Exploratory Study to Use K-means Clustering for Gesture Selection of Force Myography Upper Limb Data in Participants with Cerebral Palsy

by

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Ethics Statement

The author, whose name appears on the title page of this work, has obtained, for the research described in this work, either:

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Abstract

Many with Cerebral Palsy (CP) use assistive devices to perform daily activities. A gesture recognition based wearable device can be implemented using force myography (FMG). However, little research has been done regarding gestures to use with populations that exhibit physical disturbances associated with CP. The research presented in this Thesis lays the groundwork for implementing k-means clustering to conduct gesture selection for a FMG wearable device in a clinical setting. The concept was tested with ten healthy participants and then validated in a pilot study with a CP participant. The results from both population studies showed that the k-means clustering is able to determine the ideal gesture subset in a shorter computation time than testing machine learning models with all the possible combinations of gestures. A finally study explored online testing with three healthy participants controlling a line-following robot with the FMG band. Though this work provides the foundation for using the FMG technology to interact with individuals with cerebral palsy, additional studies are required to determine its full potential.

Keywords: Assistive devices, assistive technologies, cerebral palsy, clustering algorithms, force myography, gesture recognition, machine learning

Dedication

To my parents for their love and support.

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List of Acronyms

AAC	Augmentative and Alternative Communication
ACS	Active Class Selection
ADL	Activities of Daily Living
ANN	Artificial Neural Network
ASL	American Sign Language
AT	Assistive Technology
BCI	Brain Computer Interface
BJT	Bipolar Junction Transistor
CP	Cerebral Palsy
ECoG	Electrocorticogram
EMG	Electromyography
FMG	Force Myography
FreqE	Extensions Frequency
FSR	Force Sensitive Resistor
IMU	Inertial Measurement Unit
kNN	k-Nearest Neighbor
LDA	Linear Discriminate Analysis
MASC	Manual Ability Classification System
MMG	Mechanomyography
PRO	Proportional Sensor Type
SBC	Switch Based Control
SNR	Signal to Noise Ratio
SVM	Support Vector Machine
TCP	Transmission Control Protocol

Chapter 1. Introduction

1.1. Chapter Overview

This Chapter outlines the motivation and objectives for this Thesis. Finally, the overall layout for the Thesis is given.

1.2. Motivation

Cerebral Palsy (CP) is one of the most common childhood neurodevelopmental disabilities [1], [2]. It affects almost 2 per 1,000 live-births. It is the result of a lesion in the immature brain or fetus that occurs during gestation, delivery, or after birth [1], [3], [4]. Often considered as an “umbrella term” for a number of conditions, many clinicians will have their own working definition of CP due to the wide range of possible symptoms, such as spasticity, poor balance, and limited motor control [5], [2], [6]. There are 3 main types of CP; 1) spastic, 2) dyskinetic, and 3) ataxic [7]. Spastic CP is often associated with functional limitations and an increased resistance in muscles and connective tissue due to hyperactive reflexes and/or non-reflex changes [8]. Often, upper limb function is restricted by abnormal posture [9]. Ten to 15% of cases of CP are Dyskinetic and have trouble controlling the upper and lower limbs [7]. Usually dyskinetic CP is associated with involuntary muscle movements, dystonia, and choreoathetosis [10]. Dystonia is associated with sustained or intermittent contractions that cause twisting and repetitive movements [10]. Rapid, jerky, and fragmented movements are described by chorea, and athetosis is for slower dynamic, twisting movements [10]. Ataxic CP, the rarest form of CP [11], is associated with balance, coordination, [12] and fine tuning of movements [13]. It may cause intentional tremors when attempting movements [13]. Every case of CP is unique and it is possible for a single person to have multiple forms CP, which is known as Mixed CP [13]. A continuing challenge of CP is deciphering different symptoms and developing a classification system to evaluate the range of severities [14].

Although CP is a lifelong disorder many interventions and rehabilitation strategies focus on childhood, as early adoption has been shown necessary for positive outcomes [15]. Along with long-term physical disabilities, individuals with CP may also suffer from

speech and/or cognitive impairments [3]. These impairments may cause serious limitations in activities of daily living (ADL), such as eating, dressing, hygiene, and communication [3], [16], [17], [4]. This often leads to isolation, passiveness, and inability to control their environment [3], [16], [17]. Heath-care professionals and researchers have been focusing on possible interventions to increase ADL [4]. Many individuals with CP will use assistive technology (AT) or Augmentative and alternative communication (AAC) tools to interface and interact with their environment.

ATs may be any tool, equipment, or device that improves the quality of life, functional independence, participation, or communication [18]. Numerous technologies have been explored for use, including push-buttons (single-state switches), brain-computer interfaces (BCIs) and eye tracking [19], [20]. ATs may be categorized into six groups based on functionality; 1) communication tools, 2) computer access tools 3) adapted toys, 4) mobility aids, 5) sensory supports, and 6) instructional supports [21]. ATs are rarely used in isolation and tend to be part of a solution that is tailored for each individual and their specific needs [22]. New technology and the use of pattern recognition have increased the number of available options, such as a camera-based tracking systems that can monitor a user's movements and can pick up on small motions, such as facial features or fingers. Wearable assistive devices are advantageous because those with visual impairments may also utilize the device, since spatial accuracy is not required and the device may be worn anywhere on the body [23]. Additionally, many studies have been able to show that an increase in upper-limb activity for individuals with CP and other neurological conditions may lead to a better quality of life [24], [25]. Research in the field of gesture recognition began in that 1980s and with improvements in accuracy and increased reliability gesture recognition gained popularity with healthy populations [26]. Assistive devices are currently being researched and developed using accelerometers [23], flex sensors [27], optical systems [28], and electromyography [19]. With the use of micro-computing and micro-machining technology, the cost of sensors, such as accelerometers and inertial sensors, have decreased while accuracy has increased [29], [30].

Inertial sensors have been used in research studies to classify gestures with healthy participants [31], stroke survivors [32], and with CP populations [23]. Inertial sensors may also be used to monitor and characterize physical activity [33]. Biswas, D. et al. [32] proposed a solution that placed accelerometers at the wrist to monitor ADL

with four stroke participants and four healthy participants [32]. The participants were required to complete three tasks: 1) reach for an object, 2) lift up an object, and 3) tilt an object [32]. To collect training data, the participants completed the tasks in a controlled environment. After using sequential forward selection techniques, the data was clustered using k-means clustering into 3 groups [32], followed by 10 runs of 10-fold cross validation on the training data to determine the best feature combinations [32]. This study found that the minimum accuracy for detecting the arm movements associated with each task was 80% for healthy participants and 60% for stroke survivors [32].

Electromyography (EMG), mechanomyography (MMG) and force myography (FMG) are common myosignals that have been used with pattern recognition. EMG signals are commonly used as assistive switches. Electrodes are placed on the surface of the skin to measure muscle contractions. These contractions are to be mapped to access controls using a variety of pattern recognition algorithms [34]. A study was conducted with 10 healthy participants that used 4 electrodes, to acquire EMG signals from 5 facial movements [35]. Each movement was mapped to a different cursor movement on screen while participants were asked to complete a typing and a drawing task with the objective of creating a hands-free computer interface. The path efficiency for the healthy participants was 80.4% with a median input rate of 5.9 letters per minute for the typing task and a median classification accuracy of 98% for the drawing task [35]. Likewise, MMG uses microphones and similar sensors to monitor vibrations of muscle movements. FMG research has shown to be highly reliable, inexpensive, and has low-complexity signal acquisition [36]. The research presented in this Thesis acquired FMG signals using force sensitive resistors (FSRs) to measure volumetric changes at the surface of the limb [36]. The benefits and drawbacks are detailed in Chapter 2.2.

FMG has been widely researched in healthy populations [37], with amputees [38], and to monitor rehabilitation after a stroke [39]. An initial study by Xiao et al. [24], towards developing an FMG band was able to classify 6 gestures associated with drinking water with an real-time feedback system with an average accuracy of 92.3±3.19% [24]. Subsequently, a preliminary study [40] developed a virtual piano controlled by an FMG band with an inertial measurement unit (IMU). The objective was to allow individuals with motor impairment(s) may play music as part of therapy or as part of an at-home rehabilitation program. Another study examined using the FMG band as a controller for peripheral devices for aging population and was able to achieve a

good classification accuracy with an online linear discriminate analysis classifier (LDA) [41]. Although FMG has been successful in other applications, to the best of our knowledge, no research has been reported on FMG technology in CP populations. We believe FMG-technology can be an alternative to EMG based-systems that may be beneficial to some individuals with CP. We designed a pilot study with an individual with CP to determine the feasibility of classifying gestures using FMG signals.

Most FMG approaches use common hand gestures from ADL or American sign language (ASL) [42]. However, individuals with CP have varying abilities of fine-finger movements, gross motor skills, and range of motion [43]. Subsequently individuals with CP may not be able to perform the suggested gesture. Nonetheless, individuals with CP may be able to reliably contract muscles that can be classified using different machine learning algorithms. Therefore, clinicians need a way to determine which gestures are possible, comfortable, accurate, and linearly separable for each individual user. One-way is to generate machine learning models for every possible combination of gestures and to choose the selected combination based on testing accuracy of each model. However, this would mean that for example, to select 5 out of 10 gestures a total of 210 models would need to be trained and tested. This would be very time consuming, even with the latest computing technology. Additionally, clinicians should be able to determine the maximum number of reliable gestures that can be classified using an FMG-assistive device. This cannot be determined using machine learning models because the number of input classes need to be equal to the output classes. We are proposing a method to implement a clustering algorithm to find the number of ideal gestures and to choose a sub-set of gestures for an individual. This idea was based on the concept of local clustering.

In data mining, local clustering is implemented to handle an imbalanced class distribution. For example, while monitoring network traffic, only a handful of instances are malicious compared to regular traffic [44]. First, clustering algorithms divide the dataset into large clusters and then further cluster each subclass. Local clustering is often implemented with one of the oldest yet most popular algorithms called k-means clustering [44]. The k-means clustering algorithm is a simple iterative method that divides the dataset X into k clusters [45]. Each data point is assigned the closest cluster, reassigning clusters until the algorithm converges with the lowest squared Euclidean distance [45].

K-means clustering has been adapted over the years for specific needs and is quite robust. A study by Maharani et al. [46] investigated the use of k-means clustering to classify upper limb movements captured by the Kinect v2. Four gestures were classified: 1) forward, 2) right, 3) left, and 4) stop [46]. The Kinect v2 was used to capture the skeletal joint positions. After some initial preprocessing, the data was clustered into four groups in a way that minimized the Euclidean distance. A support vector machine (SVM) model was also trained to compare the k-means accuracy. The SVM model had an average accuracy of 95.15% in 10 ms while the k-means clustering method took only 4.45 ms, and had a test accuracy of 77.42% [46]. In another study, k-means clustering was used to create a scale of severity of physical impairment [47]. The study used kinematic and EMG data of upper limb function from 13 children with spastic unilateral CP and 6 healthy children [47]. The data was clustered into four groups; each cluster corresponding to a different severity. The results of this study were mapped to the clinical standard manual ability classification system (MACS) [47]. Therefore, due to its ability to deal with complex clusters and the varied use in gesture recognition, k-means clustering was chosen to be the primary step to perform gesture selection. This lead to the research question:

> *Can k-means clustering be used to lower computational time of gesture-selection for FMG upper limb data?*

Another study was designed, with healthy participants, to capture FMG data and select gestures sub-sets using the training data. The results of the healthy participants' study illustrated how k-means clustering can be used to select gesture sub-sets. Subsequently, the gesture-selection method was applied to the CP data collected in the pilot study to examine the feasibility of applying gesture selection to CP populations. A final study applied the k-means gesture-selection method to show healthy participants using the selected gestures to control a line-following robot with online testing. The ultimate goal of this Thesis is to lay the foundation for developing a custom wearable FMG assistive device and a tool, using k-means clustering, to be able to select gesture sub-sets for individuals with CP.

1.3. Thesis Objectives

Based on the motivation and scenario presented in the section above, this Thesis seeks to explore the use of k-means clustering to perform gesture selection using FMG

upper limb data. There are three main objectives that make up this Thesis. These objectives were fulfilled over three studies; two with healthy participants and with one participant with CP.

Objective 1: Determine if an FMG band may be used to classify upper limb movements in participants with CP.

Objective 2: Conduct a preliminary investigation to determine if k-means clustering could be implemented to lower computation time of gesture selection for FMG upper limb data.

Objective 3: Explore using k-means clustering to lower computational time of gesture selection in upper limb FMG data from participants with CP.

1.4. Thesis Layout

The remainder of this Thesis is organized into six Chapters. In Chapter 2, the background and related literature is presented including other comparative assistive technologies and discussion on FMG. Followed by a detailed discussion on k-means clustering and a summary of the three machine learning algorithms used in this study.

Chapter 3 contains the design, experimental methods, results, and implications of the study designed to meet **Objective 1**; to use FMG as an assistive device. The results of classifying FMG participant data using three machine learning algorithms are presented along with a detailed explanation of the implications and any limitations of the study.

In Chapter 4 the implementation of gesture selection using k-means clustering is explored. This initial work was conducted over a single study with ten healthy participants. In this study, FMG upper limb data were collected in order to perform gesture selection using k-means clustering. The results were compared to three machine learning algorithms on average accuracy and computational timing. This study was conducted to meet **Objective 2;** performing gesture selection using k-means clustering.

After testing the proposed tool of gesture selection using k-means clustering, Chapter 5 describes the results of performing gesture selection on the previously collected CP data from the initial pilot study. The results and implications are given in detail, intended to meet **Objective 3**; using k-means clustering for gesture selection with participants with CP.

To test the results of gesture selection with online testing a smaller study with three healthy participants was conducted. Participants were able to perform the selected gestures to control a line-following robot in real-time. The design, experimental methods, results, and implications are outlined in Chapter 6. This work provides the background and may be used as the foundation of a larger study with CP participants to further evaluate the k-means clustering method of gesture selection and the robustness of the FMG band as an assistive device.

Chapter 7 provides a complete summary of the Thesis. The discussion relates the results of three studies together. Finally, future research suggestions for FMG-based assistive devices are outlined

Chapter 2. Literature Review

2.1. Chapter Overview

In this Chapter, sources of literature related to the motivation and objectives of this Thesis are presented. First, background information on assistive devices is given, followed by a description of AT commonly used by CP populations. Next, FMG is discussed further as an AT. Then an overview of the k-means clustering algorithm and common uses are mentioned, followed a description of the three different machine learning algorithms: LDA, SVM, and kNN. Finally, a summary of the findings from literature is discussed.

2.2. Assistive Technologies and Assistive Devices

In order to increase participation within their family and in their community, individuals who suffer from physical disabilities may use AT and/or assistive devices [30]. The goal of any assistive device is to translate a user's intentions into specific actions that could assist with communication, environmental interactions, and/or play [28]. An individual may use a combination of ATs depending on their abilities and the environment to increase their independence, social interactions and quality of life [22], [18]. A common finding is that about 30% of assistive devices are abandoned [18] and a review study on ATs outlined some top concerns: 1) cost of the device, 2) number of repairs, 3) storage space, and 4) reliance on power [21]. Any successful technology must be safe, robust, easy, comfortable to use (or wear), and most importantly provide feedback [18], [30], [48]. The appearance of the device is also very important, as it may be worn on an individual or close to them at all times [18]. School-aged children also want a device that doesn't ostracize them from other students [49]. In addition, researchers found that providing training on the AT to caregivers and families increased the adoption rates. This was especially true when caregivers thought of the assistive device as an investment into the future of the user [43]. When communication solutions are given to child early it could promote the development of spoken languages [50]. Since the success of any AT or assistive device relies on many factors it is challenging to compare technologies and evaluate accuracies [50]. Healthcare professionals

reiterate the biggest challenge is to find suitable ATs for each individual, based on the person's ability, comfort, and need [19].

Assistive devices include a vast range of products, from adapted pencil grips to high-end machine vision systems [18], [30]. Assistive devices could be used in the community or at a clinic. However, an emerging market are solutions that could be integrated to be used at-home [28]. Most AT could be grouped by use: 1) Communication tools, 2) Computer Access tools, 3) Adapted toys, 4) Mobility aids, 5) Sensory Supports and 6) Instructional supports [21]. Communication tools are often grouped under AAC devices. Computer Access tools are devices that could interface with a computer and provide the functionality of a mouse and/or keyboard [21]. Adapted toys have been augmented in such a way that children could use switches to operate them [21]. Mobility aids offer physical assistance to help stabilize a position and/or move such as leg braces, power wheelchairs, and walkers [21]. Sensory support could be any AT that provides visual and auditory assistance, such as hearing aids, screen enlargers, or closed-captioned TV shows [21]. Finally, instructional supports are software programs or apps that help with accessing information, for example through speech-to-text etc. [21]. The following sections describe ATs commonly used by individuals with CP for communication and computer access.

Most communication and computer access tools could be categorized into two groups, based on functionality: 1) switch based control (SBC) and 2) proportional senor type (PRO). Though SBC and PRO serve different functionalities, they could be combined to increase the number of possible interactions for a user. SBCs describe a binary command while PROs represents multiple binary commands [19]. For example, moving the mouse cursor on a screen could be controlled with a PRO, while a SBC will control the mouse click buttons [19].

2.2.1. Mechanical Switches

A common assistive device used by individuals with CP is a simple mechanical switch. Sometimes called single-state switches, they have only "on" and "off" states, and are similar to click buttons. An example of a commercial single-state switch, known as the Jelly Bean, is shown in Figure 2-1. Single-state switches are relatively inexpensive and come in a variety of sizes. Commercial switches usually use a 3.5 mm mono audio

jack plug to connect to the peripheral device. Newer “wireless” versions come in two parts: 1) a Bluetooth enabled switch and 2) a Bluetooth reader with the audio jack. These switches could be used to operate toys, appliances, communication devices, or computers [17].

The simple switches may be quite challenging for individuals with spasticity, hyperkinetic movement, limited range of motion, and hypotonia [28]. Furthermore, the switches need to be placed proximal to the user and users may face difficulty accurately hitting the target due to spatial tremors [28]. These switches could be difficult to repeatedly activate and release with the necessary force. These, issues were part of an 11-point assessment for switches presented in a review study conducted by Angelo [51] with addition points including: efficiency of movement, safety, and ability to react in a timely manner.

Figure 2-1: Commercially available Jelly Bean switch used by individuals with disabilities to connect to a peripheral device. Reproduced with permission from [52]

2.2.2. Scanning Method

Over 40% of children with CP have difficulty communicating [50]. This is a huge challenge for therapists and it has been identified as a top priority. Studies have shown that communication impairments could delay language development, decrease peer-interactions, lower self-esteem, and a lower quality of life [50]. Assistive devices that help with communicating choose can range from mid-ranged static displays with one level of choice to higher-end devices with multiple levels of choice [50]. There are two

main selection processes available; 1) the scanning method and 2) the pointer system (mouse, head-tracking, eye-tracking). The scanning method in many cases is the only way for those with severe disabilities to communicate [53].

The scanning method has been implemented in a variety of ways. Ultimately, it is a way to systematically offer a user different options to choose from to produce a sentence and/or communicate a desire. Often, the choice is made using a single-state switch [20]. For the visually impaired, auditory scanning can be done by playing back audio clips. In 1998, a symposium was held to discuss the scanning method and attendees were invited to try to use auditory scanning devices. The attendees were blindfolded to simulate the experience many users face. Many attendees had difficulty using the system and this was considered a pivotal moment for advancements in user interfaces for AAC systems [54].

Devices that implement the scanning method need to look at the speed at which choices are presented. Intuitively systems that scan quicker, result in faster communications. However, users may miss a desired item and need to wait till it reappears again. If the device is too slow, the attention of the user may wander off. Therapists try to set a desired speed for each user. However, the desired speed may change over time due to fatigue and/or concentration of the user. If single-state switches are used, the scanning method may be quite slow. However, the single-state switches are inherently quite simple and remain a reliable AAC solution [55].

Nowadays, with increase of mobile phones and tablets, AAC are more widespread. Many phones, laptops, and tablets have accommodations such as reading out information on a screen, increasing text size, and sequentially highlighting menu items [50]. There is now a shift towards mobile phone AAC tools rather than traditional systems. These applications may customize the experience for a user by providing a combination of audio and/or image cues in different languages [50]. They are usually cheaper than a dedicated AAC devices [50]. This is heightened by the multi-functionality of mobile devices to access the internet, send text messages, and emails [50].

2.2.3. Brain Computer Interfaces (BCI)

Brain-computer interfaces (BCIs) refers to a collection of technologies that can interpret recorded brain activity into device controls [56]. Individuals who benefit the most from BCIs have severe motor disabilities are not able to communicate or control muscular activity. However, their cerebral activity is still functioning [19]. BCIs may be invasive or non-invasive [19]. Invasive technologies, such as electrocorticogram (ECoG), have better Signal to Noise Ratio (SNR) and higher-dimensional control. However, involve a higher clinical risk and are used only when non-invasive options are not possible. Electroencephalography (EEG) is considered a non-invasive BCI, as it can be used to translate brain activity into a desired command. EEG signals may be used to control a cursor as PRO using a continuous cerebral wave [19].

A popular subtype of BCIs are eye-tracking or gaze-based assistive technologies that use eye trackers to controller a computer [57]. An infrared system illuminates the eyes and the system tracks the pupil-corneal reflection [58]. Assistive devices that use cameras and/or infrared sensors to monitor gross motor movements, fine muscle movements, facial expressions, or eye-gaze may be very comfortable to use as there nothing to wear, and no risk of skin irritations from wearing sensors or adhesives [59]. This may be quite beneficial for those with severe disabilities. There are several commercial eye-tracking products available. However, studies have only been conducted on a small sample basis [50]. Eye-tracking assistive devices are part of the PRO type as they can control multiple commands. Furthermore, eye trackers face a challenge deciphering between voluntary and involuntary head movements, commonly associated with CP [60]. Wheelchairs or equipment may block an unobstructed view to capture the user’s eye [60]. Multiple cameras may assist with those challenges. However, the portability of the setup is hindered [60]. Although many systems require a successful calibration to achieve higher accuracy, individuals with profound disabilities may have difficulties maintaining head position and eye contact for a long time in order to complete the calibration process [60]. Another camera-based system is a head tracking camera, which may be used by individuals with severely limited upper limb movements. A small reflective dot is placed on the user’s head, and a camera that is placed on top of the computer monitors head movements [61]. Those movements are then translated to computer cursor movements. Head tracking cameras are an example of PRO type assistive devices.

2.2.4. Wearable Assistive Technologies

A wearable assistive device can be worn directly on the body and relies on a user's motor capabilities. Over 60% of children with CP are visually impaired and the precise motor control needed to operate single-state switches is not possible [23]. Wearable devices are not affected with sensor misalignment issues, commonly associated with vision-based and externally mounted systems [62]. Additionally, the device is less likely to be misplaced [41]. Depending on the user's abilities, a wearable device may map a single gesture to an access control or a series of gestures to many different commands. Muscle movements could be acquired with a variety of sensors such as inertial sensors, flex sensors, EMG, MMG, and FMG. The signal are converted into actions with the use of machine learning.

An inertial sensor-based system was proposed by Qiao et al. [23] that uses a single kinetic sensor (accelerometer and gyroscope). The system was able to classify four basic gestures with good accuracy [23]. Other researchers [29] have used accelerometers attached to the head to operate a computer mouse within 1° accuracy. However, the study also showed fine motor control were difficult for participants with CP. An underlying issue with inertial sensors is that they suffer from time varying biases and noise. This may cause a drift and produce an unreliable signal within a few seconds [31].

Accelerometers are also used as part of other ATs. Vocal cord vibration switches are used by those with severe motor impairments, nonetheless are able produce vocalizations [63]. The vocal cord vibration switches work by placing an accelerometer on top of a user's larynx and connecting it to a microcontroller-based processing unit. The accelerometer signal is analyzed for humming and the microcontroller maps the humming to an access control [49]. A similar AT places an accelerometer against the anterior part of the ear near the tragus (Figure 2-2 describes the anatomy of the ear and the location of the tragus) to monitor tooth-clicking. The accelerometer signal is filtered in a data processing unit and transient vibrations that are created by the sudden click of bringing the upper and lower jaw together are monitored. Usually, this clicking action will register as a spike of energy at the accelerometer location. Often, the tooth-click drive system is paired with a head tracking camera system as a full solution to a computer mouse [61].

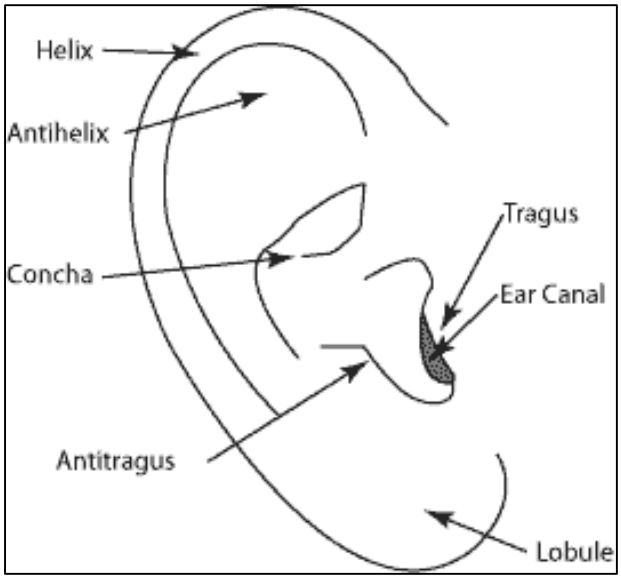

Figure 2-2: Describes the anatomy of the outer ear, note the location of the tragus in relation to the rest of the ear. An accelerometer may be placed near the tragus to monitor tooth-clicking. Reproduced with permission from [64]

A sip-and-puff switch by Origin Instruments Corporation is an assistive device that offers hands-free access using the SBC method by sensing the difference in air pressure. Figure 2-3 shows the Sip/Puff device, a longer tube with an attached mouthpiece that would be placed near the user's mouth using a headset. The USB connection is used to connect the device to a computer [65]. To operate the switch a user can sip or puff air into the mouthpiece [61]. The switch is configured to map the sips and puffs to mouse clicks or keyboard strokes [61], [66].

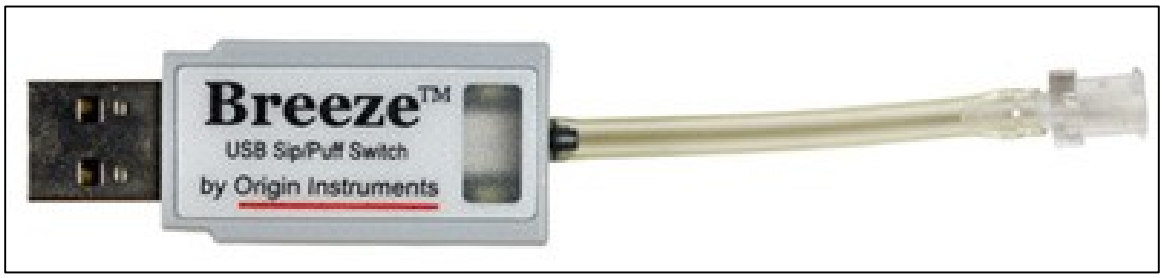

Figure 2-3: A USB Sip/Puff Switch by Origin Instruments. The switch senses the difference in air pressure created by sips or puffs of air. Reproduced with permission from [65]

A tongue drive wearable device has been developed in recent years to convert tongue movements into controls [67]. The user needs to secure a small (size of a grain of rice) magnet to their tongue using tissue adhesives, tongue piercings, or implantation [66]. The system will detect movements made by the user's tongue, with an array of magnetic sensors mounted on a headset [66]. These signals may be sent wirelessly to a

smartphone, personal digital assistant (PDA) or nearby laptop. A signal processing algorithm classifies the movement into access controls [67], [68].

Flex sensors can detect movements related to the bending of a joint [27]. Depending on the bend, the electrical resistance will change [27]. Most flex sensors are low-cost and light-weight. They can be used in combination with other sensors to either improve the accuracy or provide a multi-step system [69], [27]. Flex sensors have been implemented to monitor wrist extensions frequency (FreqE) which may be used as an indicator of functional hand use [70]. Often, flex sensors are embedded into gloves to measure finger movements [33]. However, most individuals with CP are not able to control their fingers and find donning a glove very difficult because of muscle stiffness or joint atrophy [27].

Electrodes placed on the surface of the skin to collect surface electromyography (sEMG) signals can be used as an alternative to switches [34]. These small devices may be attached to even residual muscles or attached to scarred skin to activate EMG signals [34]. Figure 2-4 provides an example of a commercially available sEMG switch from the company Emego on a user's forearm [71]. EMG has also been used as a way to classify functionality of upper limbs of those with neurological disorders[47]. For individuals with severe motor disabilities or spinal cord injuries the electrodes may be placed on facial muscles [19]. EMG-based assistive devices include switch-based controllers, computer mouse-emulators, and speech recognition [19]. Computer mouse emulators attempt to provide point-and-click functionality. Many studies suggest using sEMG switches as a hands-free alternative even for able-bodied users [19]. For an user with physical disabilities, the number of muscles available and dexterity control determines the strategy required to obtain the point-and-click functionality [19]. A study comparing a standard mouse, head-orientation using accelerometer, and a EMG-based mouse emulator found the EMG-based solution was inferior to other methods, due to the difficulty to move the cursor diagonally on the screen [19]. Another limitation of EMG-based systems is signal fluctuation due to variations in electrode-skin impedance [62].

Figure 2-4: Emego Commercial sEMG switch. The product is able to map muscle contractions to access controls using surface electrodes. Reproduced with permission [71]

An alternative technology that is not affected by skin impedance is MMG. MMG is considered the mechanical counterpart to EMG and uses microphone-sensors to measure low-frequency vibrations during a muscle contraction [72]. For example, an MMG switch may be placed at the eyebrow and activated by forehead contractions. MMG switches are usually placed at the surface of the skin and monitor signals that lie within the 2-50 Hz range [72]. These devices require signal processing to remove noise above 300 Hz. Hence, this technology may not be appropriate for high-pitch vocalizations in children. Furthermore, MMG switches cannot be used in environments prone to vibrations, heavy movement, or loud noise as those factors may introduce artifacts [72], [62]. One study [62] considered the signal-to-noise ratio (SNR) of MMG switch with 7 participants that suffered from severe physical disabilities. It found that the MMG switches should be used where the muscle site is intact and the number of signal artifacts is low [62]. Any conditions that cause involuntary muscle contractions or suppress muscle contractions will negatively affect the MMG switch functionality [62].

Another myosignal, often compared to EMG, is FMG, that measures the volumetric changes of a muscle at the surface of the skin [36]. As an assistive device, an FMG band was successfully demonstrated by Delva et al. [41] to be used with

seniors as a smart-home controller. Ten participants performed five hand gestures based on ASL. The data collected was used to train an LDA model. The non-senior participants had an online testing accuracy of approximately 90%, while the senior participants had an online testing accuracy of approximately 75% [41]. Further research needs to be conducted into using FMG as an assistive device in populations with physical disabilities, such as spasticity, muscle stiffness, or lower muscle tone etc. Additional information regarding the background on FMG is given in Chapter 2.3 since this FMG bands were used in all three studies detailed in this Thesis.

2.3. Force Myography

FMG involves monitoring and detecting the changes in volumetric pressure at the surface of the limb [36]. It is an unobtrusive method and that may be placed around any limb of the body without strategic sensor placement [39]. Often compared to EMG, FMG does not require the same amount of signal processing and is not affected by changes in skin-impedance. FMG signals may be acquired from a variety of inexpensive sensors: 1) pneumatic sensors, 2) strain sensors, 3) optical fiber sensors, and 4) force sensors. Pneumatic sensors are created by vacuums in polyethylene bags. Strain sensors are embedded into a stretchable band and the deformation is measured. Optical fiber sensors measure the micro-bending caused by contractions of the muscle while the sensors are wrapped about the limb [73]. FSRs are a polymer thick film whose resistance is inversely proportional to the force that is applied to its surface. FSRs have a high reliability and a low profile so these sensors have been widely used in FMG research [36]–[39], [42], [74]. Figure 2-5 is an example of a commercially available FSR with 14.7mm diameter active area. A FMG band is developed by embedding FSRs into a bendable backing that is wrapped around a limb of the body. As the muscles contract and relax the pressure applied to the FSRs changes. Those signals may be fed into machine learning classifier to train a model and then predict a muscle movement, through either online or offline scenarios.

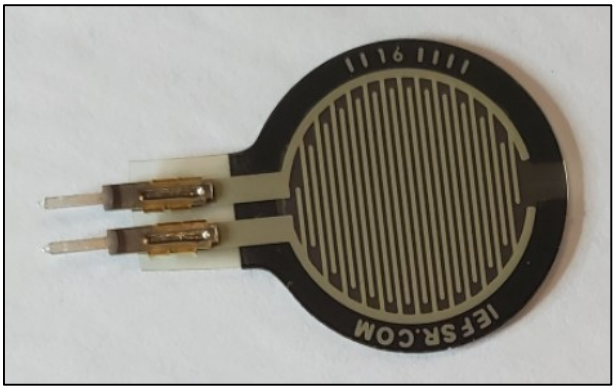

Figure 2-5: Example of a FSR with 14.7mm diameter active area

FMG has been widely used in gesture recognition [24], [26], [38], [42], [75]–[77]. Applications include rehabilitation [24], prosthetic control [38], and assistive devices [41]. Strokes are most common cause of physical disabilities, and may cause disturbances in motor-function similar to CP [78]. A study was conducted to monitor grasping with individuals after suffering from a stroke [39]. The participants wore the band while completing 20 repetitions of 3 tasks that involved reaching, grasping, and moving an object. Using a SVM classification algorithm, the FMG-based grasp detection had accuracy of 92.2% for 8 stroke participants and 96% accuracy for the 8 healthy participants [39]. High-density arrays of FSRs can also be used to capture FMG signal [76]. A study by Radmand et al. [75] demonstrated how an array of pressure sensors can be used to detect patterns between a prosthetic socket and the residual limb.

For upper limb gesture recognition, an FMG band can be placed at the forearm or the wrist. Research was done by Jiang et al. [42] to compare classification accuracies between FMG signals acquired at the forearm and the wrist, and EMG signals acquired at the same two locations. Participants performed a set of 48 gestures across 3 trials. An LDA classifier model was trained. The cross-trial accuracy for FMG band using 8 sensors was higher than sEMG [42]. Researchers were also able to show no difference between locations (wrist and forearm) for FMG signals [42]. The cross-validation accuracy for all sessions for FMG was above 91.2% [42].

Another study was done towards building an augmented virtual piano to extend at-home rehabilitation programs for those with motor impairments, such as stoke and CP [40]. Musical therapy has been shown to reduce blood pressure and lower heart rates [79]. The designed system acquired the IMU signal to determine which key and the gestures were used to map to different key combinations. The training data was used to

classify three algorithms: artificial neural network (ANN), k-nearest neighbour (kNN), and Fisher's LDA. After training the system using a combination of static and dynamic sampling, an online testing sequence was used to evaluate the system. The testing accuracy range for three classifiers was between 73% and 90%.

Although most FMG research monitors upper extremities, lower limb studies have shown that FMG bands can be used for detecting gait phase analysis and step counting [80]. Jiang et al. [81] were able to show a high gait phase detection accuracy of over 99.9% and a short temporal error of 2.1%. In a second study, unsupervised learning techniques were implemented with the k-means clustering algorithm to measure step-count [80]. The model was able to cluster data from an FMG band with 8 FSRs into 3 different walking speeds. FMG signals have also been regressed to estimate finger forces [37], [82], grasping [39] and estimating hand force/torque [83], [84]. Sakr, M. et al. [83] explored the use an FMG band in dynamic condition to measure FMG signals and predict exerted force. Three regression algorithms had accuracies of 92%, 90%, and 79% for kernel ridge regression (KRR), support vector regression (SVR), and general regression neural network (GRNN) respectively [83].

Based on the gaining popularity, inexpensive technology, and the future potential of FMG as an assistive device, exploratory studies towards building a wearable FMG band with CP populations is necessary.

2.4. K-Means Clustering

2.4.1. Clustering Overview

Clustering algorithms aim to find meaningful groups that share common characteristics [44], [85]. Clustering algorithms have wide applications, for example in market research. Market researcher use clustering for large-scale customer segmentation, profiling, and to locate target demographics. Most clustering algorithms may be grouped into various categorizes. An overview of the grouped algorithms is given in Table 1.

Table 1: An overview of clustering algorithms

Clustering Algorithms	Description
Density-Based Algorithms	Clusters are taken as a dense region of data objects surrounded by regions of low densities. These algorithms are advantageous when the clusters are irregular, overlapping, and when the data is noisy and has outliers [44]
Graph-Based Algorithms	Data objects are considered nodes. The distance between two objects as the weight of the edge connecting two nodes. This is represented by a graph where each subgraph is a cluster. Agglomerative hierarchical clustering (AHC) algorithms merge two nodes close together iteratively, until all nodes are connected [44].
Hybrid Algorithms	Two or more clustering algorithms may be combined to overcome limitations of a single algorithm. These algorithms may lead to surprising clusters that provide good performances for specific applications [44].
Algorithm-Independent Methods	These algorithms cluster the results of other clustering algorithms, not the input data itself. They try to find a single partition that matches every other partition given. Some algorithms employ metaheuristics to improve results, although this comes at a higher computational cost [44].
Prototype-Based Algorithms	This category includes popular algorithms such as k-means clustering (KMC) and fuzzy c-

	means (FCM). These algorithms learn about a prototype or centroid, and form clusters around the centroid [44].

2.4.2. K-Means Clustering

Research on k-means clustering dates back to the middle of the last century. The k-means clustering algorithm is a iterative method that divides the dataset *N* into *k* clusters [45]. Each data point is assigned the closest cluster, reassigning clusters until the algorithm converges [45]. Table 2 outlines the steps performed by the k-means clustering algorithm. The initial cluster locations (centroids) can be selected randomly setting them to be the solution of clustering a smaller subset or the global mean of the data *k* times. The algorithm is said to converges when the Euclidean distance is minimized. Assigning data points to a cluster and by assuming spherical covariance, the k-means algorithm is considered to be simpler and faster compared to other clustering methods.

Table 2: K-means Clustering Algorithm

K-means Clustering Algorithm

Step 1	*Cluster centroids are randomly selected.*
Step 2	All data points are assigned to a cluster of its nearest mean and the cost function is calculated.
Step 3	Each centroid is relocated to the mean of all the data points within that cluster.
Step 4	Step 2 and Step 3 are repeated till the algorithm converges.

K-means clustering is also considered to have lower computational complexity. Some disadvantageous of k-means clustering are: it does not perform well for non-spherical covariance and is quite sensitive to outliers. However, since the k-means clustering optimization problem is still challenging and newer data tends to have higher-dimensionality, k-means is constantly being adapted into new scenarios [44].

2.4.3. Local Clustering

A challenge that affects classification has been predicting classes with imbalanced class distribution [44]. Detecting oil spills in satellite images, predicting failures in IT, or telecommunication systems are some fields that face this challenge [44]. A suggested method is using local clustering [44]. The idea is to take an imbalanced data set and perform two-stage clustering: once to find larger clusters and then to find subclasses within a larger cluster. Afterwards, any classifier suited for the dataset or application may be used for classification [44].

A *Smart Surface* was developed in a study [86] that used RFID tags and RFID readers to detect gestures made in front of a vertical surface. A two-step unsupervised learning data processing stage was implemented to cluster RFID antennas and passive RFID tag data. First, data were clustered into two groups: presence of an arm/hand and no presence using k-means clustering where k = 2. Then, an SVM classifier was used to further classify the data into different actions [86].

2.4.4. K-Means Validation

In supervised learning, evaluating the clustering performance can be done using the ground truth labels. However, other evaluation outcomes maybe desired, such as the ideal number of clusters for a given set of data or the degree of separation between clusters. These measures are known as internal indices since they deal with the goodness of a clustering structure without respect to external information. Two interval validation measures are present below: 1) Silhouette Plots and 2) Elbow Plots.

Silhouette Plots

Silhouette plots were first described by J. Rousseeuw in 1986 [87]. The research suggested that each cluster can be represented by an object known as a “silhouette”. Each silhouette shows if the sample in question is well within the cluster or somewhere between the clusters. A silhouette plot is constructed by finding the average distance from all data points in the same cluster a_i and computing the average distance from all data points in the closest cluster b_i, where *i* is a data sample. A silhouette coefficient is defined by equation (1) [88]. It is a unit less value that describes the measure of how similar a point is to other points in its own cluster compared to others [88]. An example of

a silhouette plot was generated with FMG data from a healthy participant. The participant performed 10 static finger and hand movements. The experimental protocol is described in detail in Chapter 4. The FMG data was clustered using Matlab's k-means function *kmeans* and a silhouette plot was generated using Matlab's silhouette function *silhouette*. The silhouette plot is shown in Figure 2-6. The average cluster silhouette coefficient for each set of *k* clusters is represented with a red dashed line.

$$S_i = \frac{(b_i - a_i)}{\max(a_i, b_i)} \tag{1}$$

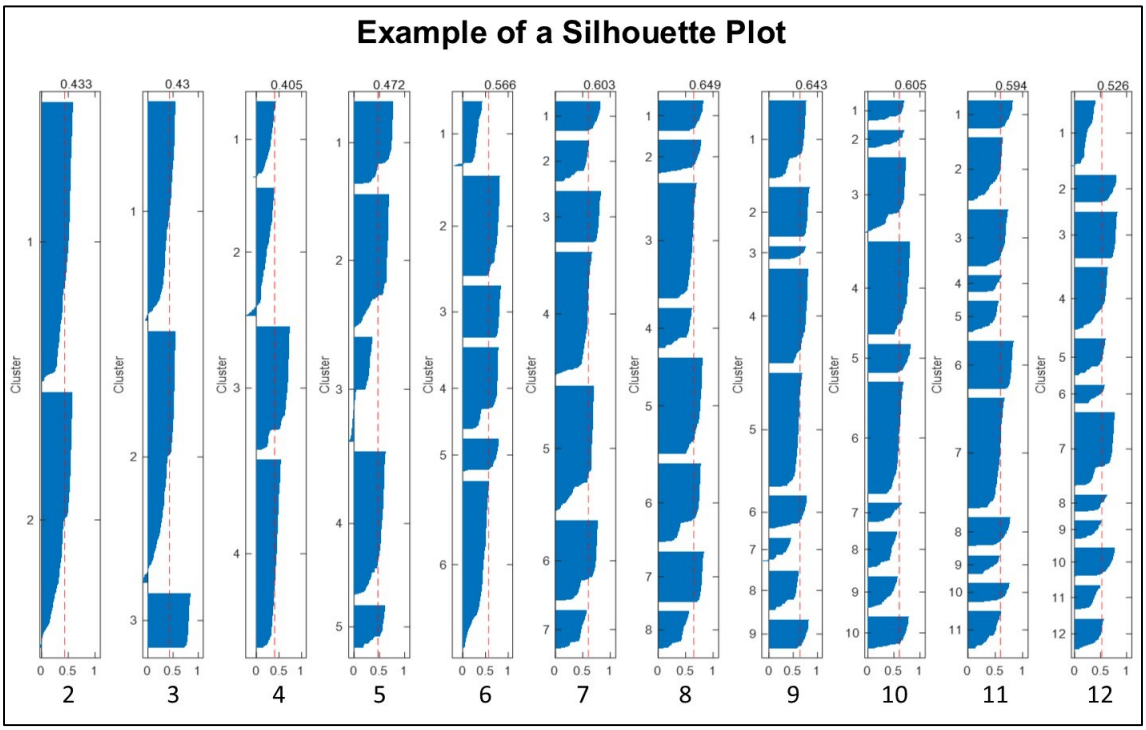

Figure 2-6: Example of a silhouette plot constructed from FMG data. left to right, k = 2 to 12.

Elbow Plots

Elbow plots are an observable way of finding the ideal number of clusters for a given dataset. An elbow plot can be generated by plotting the sum of squared Euclidean distance (SSE) between data points and their assigned centroid's for *k* clusters, where k ranges from 2 to N. An ideal value is where the graph begins to flatten or form an "elbow".

A similar method known as the average silhouette method plots the average silhouette coefficient for k-clusters, where k ranges from 2 to N clusters [89]. Using the silhouette coefficients an elbow plot was constructed and is shown in Figure 2-7 with k ranging from 2 to 12. The Matlab *Clustering Evaluation* toolbox was used to generate the plot. It is observable that the ideal number of gestures for the given FMG data should be $k = 8$.

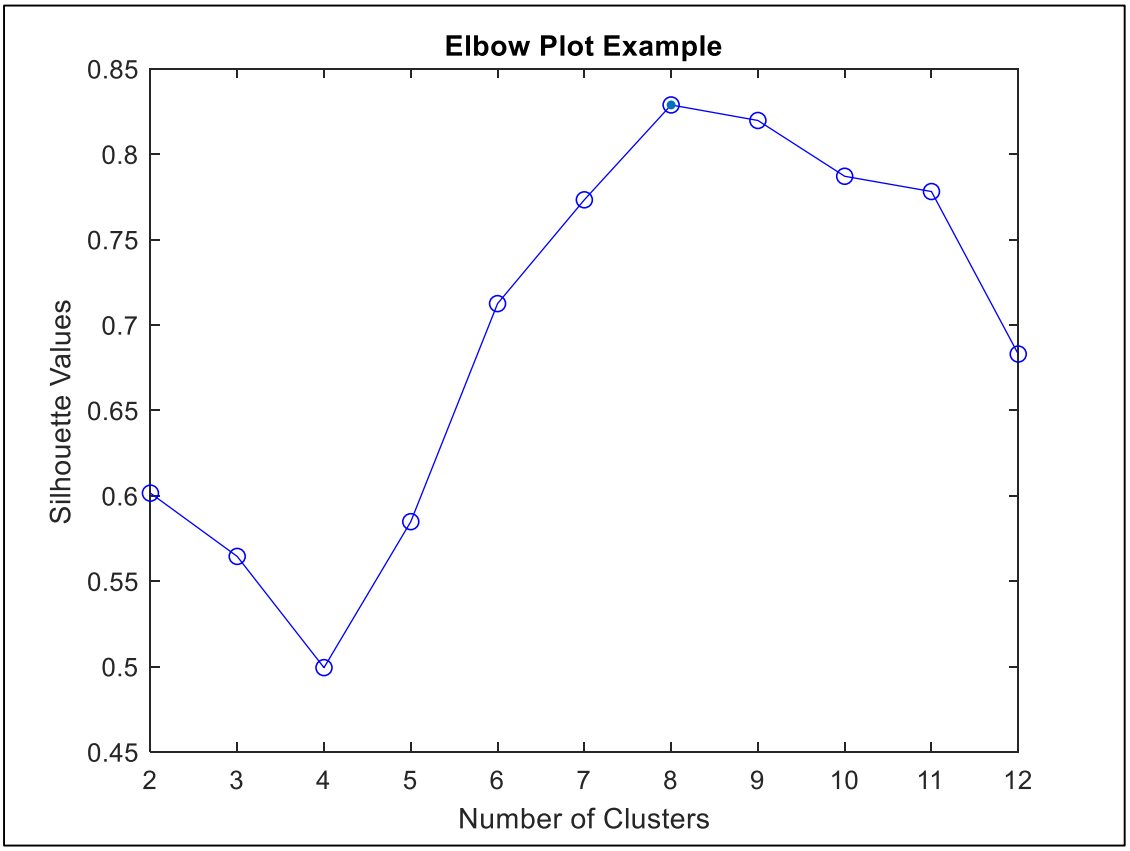

Figure 2-7: Example of an average silhouette elbow plot for FMG data with k ranging from 2 to 12. The plot begins to flatten at k = 8 therefore, it is the ideal value.

2.5. Machine Learning Algorithms

Three machine learning algorithms are commonly used with FMG data to classify muscle movements: 1) Linear Discriminate Analysis, 2) Support Vector Machine, and 3) k-Nearest Neighbour. Most FMG applications utilize supervised learning since the ground truth labels are given by an human observer, camera set-up, or an secondary

sensor. Unsupervised learning does not involve labels and groups together similar examples. It can be used to calculate the density estimation, which is the distribution of the data within the input space [90]. Semi-supervised learning uses a small amount of labelled data with a larger amount of unlabelled data to improve the accuracy [91].

In this Thesis, LDA, SVM, and kNN classifications algorithms were used to classify *k* classes and provide a comparison to the k-means based gesture selection method. To visualize the difference in decision boundaries for each machine learning algorithm, FMG data acquired from a single participant was used. The details of the experimental protocol are given in Chapter 4.3.3. There are 50 observations, with 2 FSRs per sample that correspond to 3 classes. Figure 2-8 shows a scatter plot of the labelled observations.

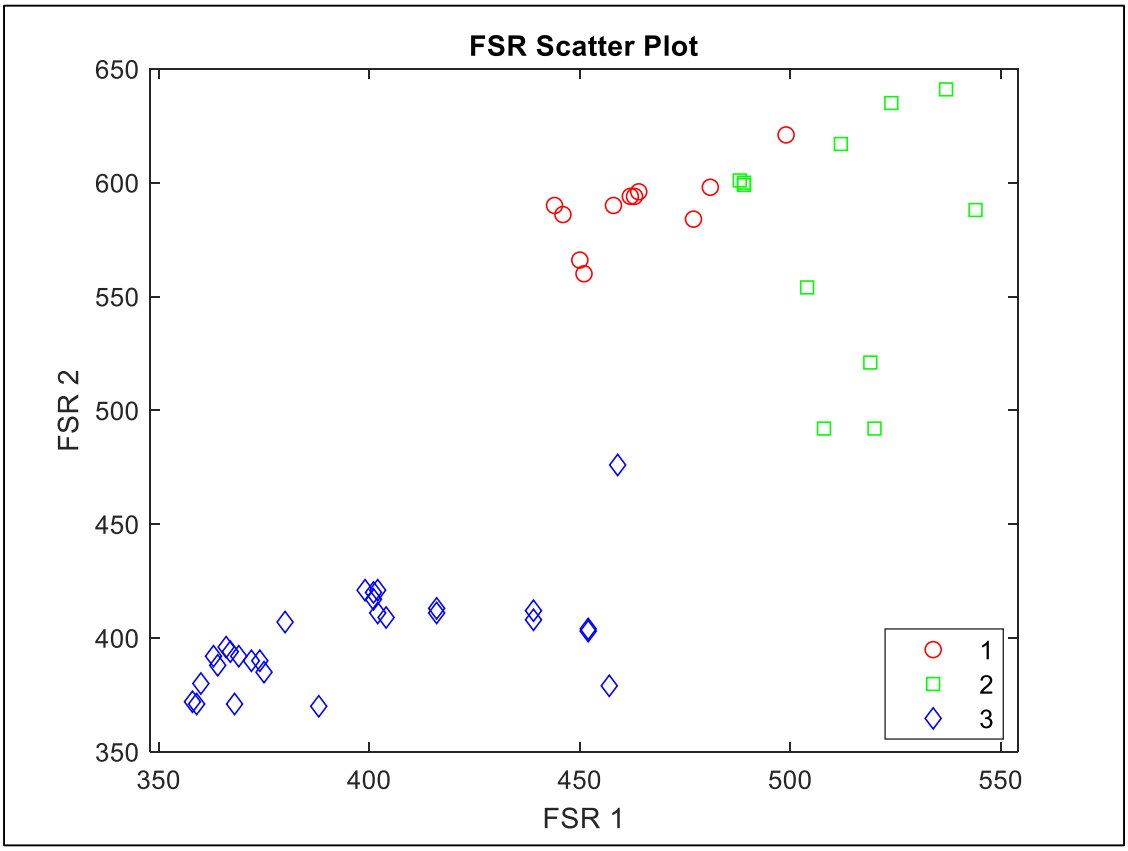

Figure 2-8: Scatter plot of data used to visualize decision boundaries between machine learning algorithms. The FMG data corresponds to 3 gestures performed by a single participant.

2.5.1. Linear Discriminate Analysis

LDA is efficient classification method that takes an input vector x and assigns it to one of k classes for which the decision surface are hyperplanes. The discriminant function y(x) for a two-class problem is shown in equation (2) [90], where w is called a weight vector and w_0 is a bias. An input vector x is assigned to class one if the discriminant function is larger than 0. Otherwise, it is assigned to class two. The multi-class problem discriminant function has the form shown in equation (3) [90]. An input sample x is assigned to the class k where $y_k(x)$ is larger than the output of all other classes. Fisher's LDA selects a one-dimensional projection that maximizes the class separation with a hyperplane. The Fisher criterion, as shown by equation (4) [90], is the ratio between-class variance s_B and within-class variance s_W (see equations (5)-(6)) [90].

$$y(\boldsymbol{x}) = w^T x + w_0 \tag{2}$$

$$y_k(x) = w_k^T x + w_{k0} \tag{3}$$

$$J(\boldsymbol{w}) = \frac{\boldsymbol{w}^T s_B \boldsymbol{w}}{\boldsymbol{w}^T s_W \boldsymbol{w}} \tag{4}$$

$$s_B = \sum_{k=1}^{K} N_k (y_n - \mu_k)(y_n - \mu_k)^T \tag{5}$$

$$s_W = \sum_{k=1}^{K} \sum_{n \in C_k} (y_n - \mu_k)(y_n - \mu_k)^T \tag{6}$$

Figure 2-9 visualizes the decision boundaries for data presented the scatter plot show in in Figure 2-8 using Matlab's linear discriminate analysis classifier.

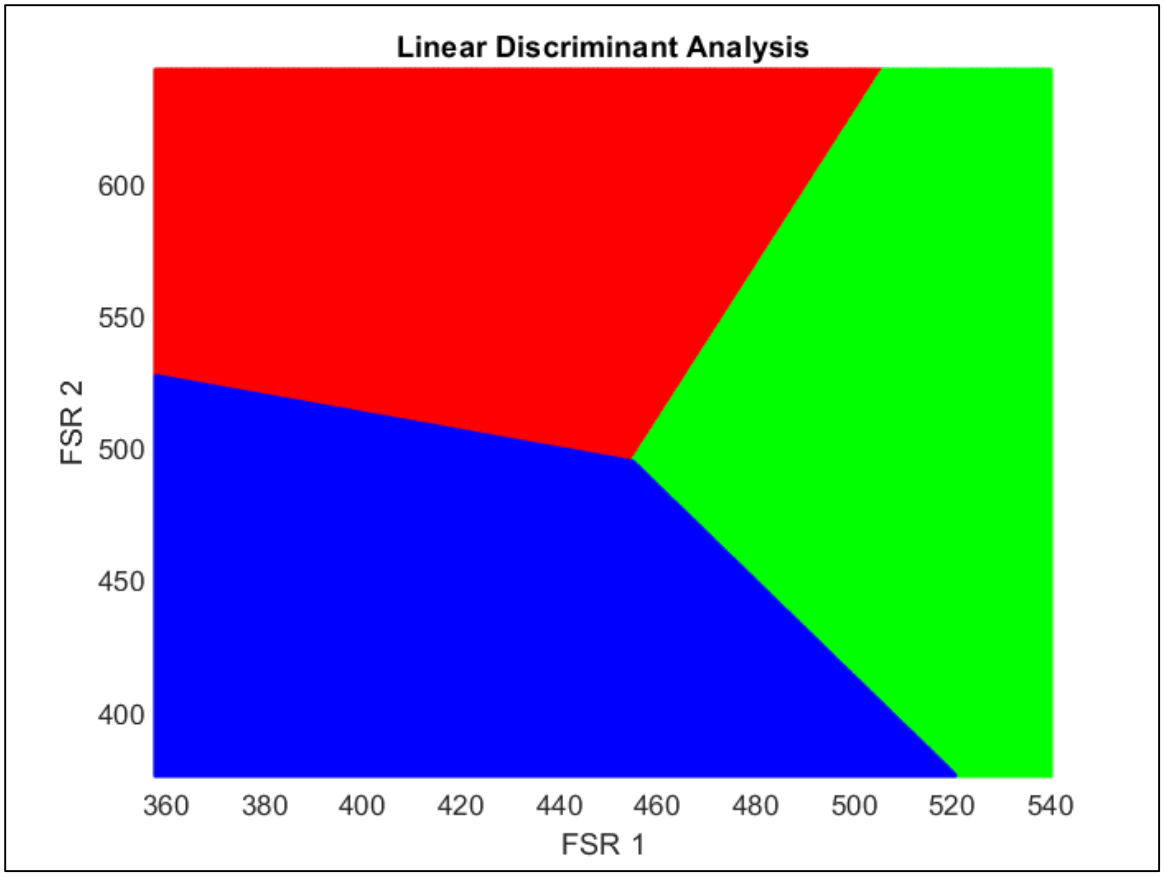

Figure 2-9: Decision boundary visualization for LDA. Fifty samples of FMG data were classified.

2.5.2. Support Vector Machine

SVM is regarded as one of the most robust and accurate binary sentiment classifications [45],[92]. The two class approach looks at finding the best classification function, where the ideal solution is found geometrically by choosing a hyperplane that passes through the middle of the classes [45]. A new instance may be classified by testing the sign of the function to determine the membership [45]. However, there are an infinite number of hyperplanes. Hence, the SVM algorithm tries to find the best solution by maximizing the margin between the two classes thus limiting the number of solutions to only a few hyperplanes [45]. Any data points that lie on the margins are considered support vectors. Once the model is trained, only those support vectors are retained [90]. To visualize the decision boundary for SVM, FMG data presented in Figure 2-8 was classified using Matlab's multiclass SVM classifier and is shown in Figure 2-10.

If the dataset in the previous optimization problem is not linearly separable, there is no solution. This can be overcome by allowing a certain amount of error. The sum of errors cannot exceed a total error budget C that is considered a tuning parameter [93]. A nonlinear kernel can be also used. Nonlinear kernels are more flexible as they can map variables into higher dimensional space [45]. Where, the same number of observations are sparser and likely to be separable. The separability improves the performances of the SVM algorithm [93]. Other kernels functions that are widely used included Gaussian, polynomial, and sigmoid kernel [92], [93].

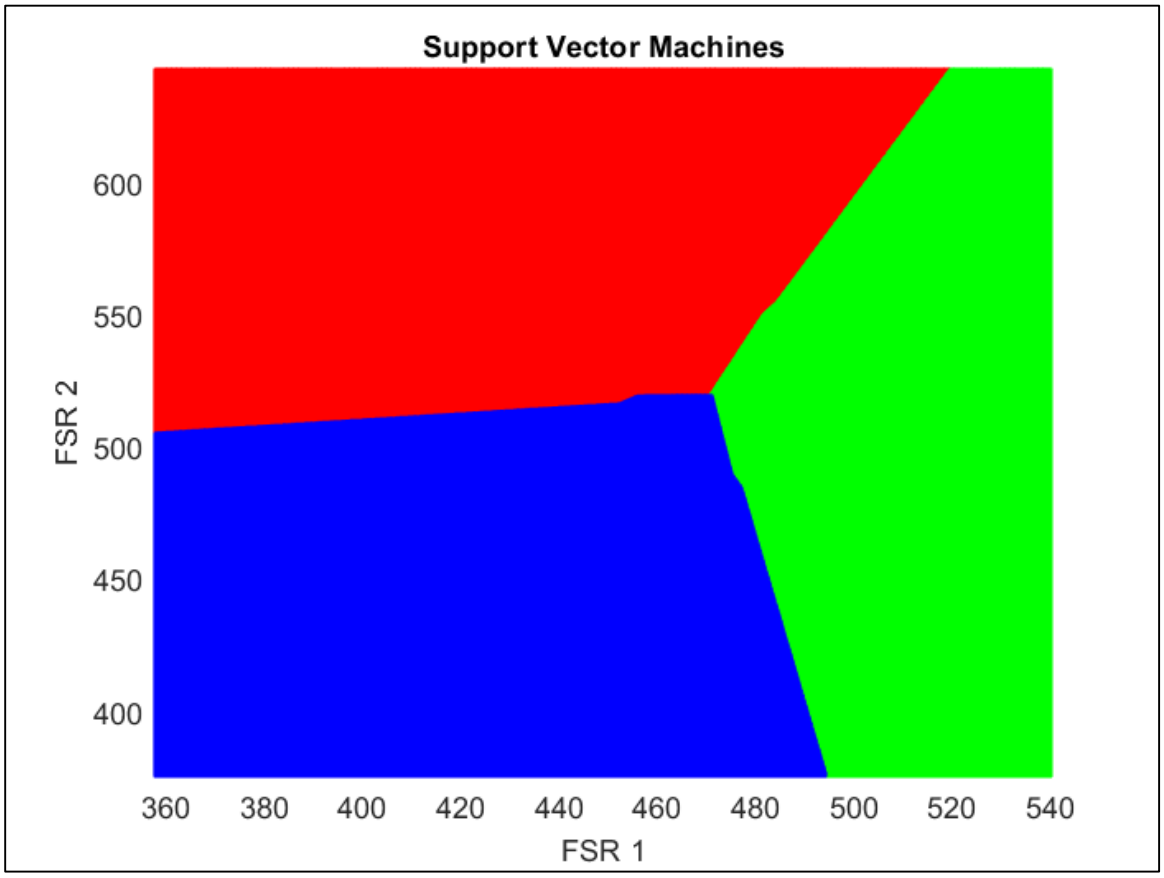

Figure 2-10: Decision boundary visualization for SVM. Fifty samples of FMG data were classified.

2.5.3. k-Nearest Neighbour

A nonparametric classification method is k-Nearest Neighbour. It is easy to implement and performs well in many situations [45]. K-Nearest Neighbour is ideal for multi-model classes and instances when an object can belong to multiple classes [45].

To classify a new unlabelled data point, the distance between the instance and the object is calculated. Then, its k-nearest neighbours are identified and the class of those neighbours are used to determine the label of the new data point using equation (7) [45], where v is a class label, y_i is the class label for the ith nearest neighbor, and I(·) is an indicator function the returns 1 when the argument is true, otherwise returns 0. This approach is known as majority voting.

$$y' = \underset{v}{argmax} \sum_{(x_i,y_i)\in D_z} I(v = y_i) \tag{7}$$

Another approach is to replace equation (7) with a distance-weighted voting shown in equation (8) [45]. This is approach is less sensitive to the number of nearest neighbours considered [45]. The weight factor w is the reciprocal of the squared distance $w_i = 1/d(x',x_i)^2$. The ideal distance measure is when the distance between two objects is the smallest, consequently the greater likelihood they belong to the same class [45].

$$y' = \underset{v}{argmax} \sum_{(x_i,y_i)\in D_z} w_i \times I(v = y_i) \tag{8}$$

One of the major considerations when choosing k-Nearest Neighbor is that the entire training dataset must be stored [90]. Storing the dataset can be computationally expensive depending on the size of the dataset. However, this can be offset by using tree structures [90]. To visualize the decision boundary for kNN FMG data was classified using Matlab's default kNN classifier with 1 nearest neighbour for each point and is shown in Figure 2-11.

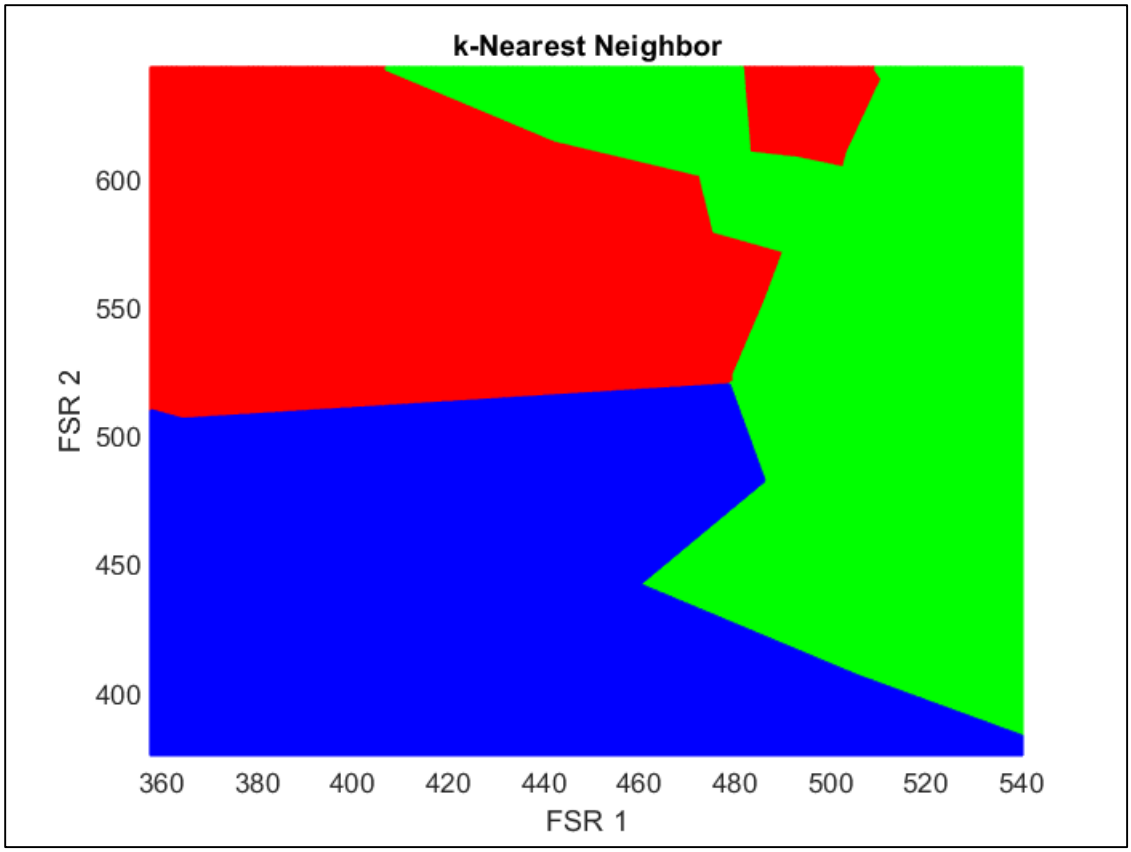

Figure 2-11: Decision boundary visualization for kNN. Fifty samples of FMG data were classified.

2.6. Summary

A variety of AT and assistive devices were explored, including single state switches, inertial sensors, EMG and FMG. These ATs may be used in combination by individuals with physical disabilities to increase their participation in daily activities, communication, and independence. The scanning method of decision making was discussed in detail. Wearable technologies that map a user's motor movement to an access control have several advantages: can be operated by individuals with severe disabilities including visual impairment and a lower possibility of sensor misalignment. FMG has been shown to have high accuracy, good reliability, and uses inexpensive sensors. Though FMG has been used in seniors, amputees, and stroke survivors, populations that suffer from severe motor disabilities are still unexplored. Given its advantages and popularity in hand-gesture recognition, FMG was chosen for this research.

To select gestures that an individual with CP can reliably perform, k-means clustering was chosen. K-means clustering is a low-complexity algorithm that has been widely used as part of an initial clustering step prior to other classifiers for scenarios where the classes are not well distributed. Three commonly used machine learning algorithms, LDA, SVM, and kNN were also outlined. The topics covered in this Chapter provided the background for the design, execution, and evaluation of the three studies presented in this Thesis.

Chapter 3. Force Myography Based Assistive Device

3.1. Chapter Overview

In this Chapter we describe the pilot study conducted as part of this Thesis. It is intended to meet **Objective 1**; the feasibility of developing a FMG band assistive device for individuals with CP. Chapter 3.2 gives an overview of the study, followed by experimental methods in Chapter 3.3 and the experimental results in Chapter 3.4. Finally, a summary of the study and implications of the results are presented in Chapter 3.5.

3.2. Study Overview

This pilot study classified the FMG data from a CP participant using three machine learning algorithms. Although gesture recognition is a widely researched topic, FMG research with CP participants has not been reported to the best of our knowledge. Five gross motor gestures were used to train an LDA, SVM, and kNN machine learning model. The models were able to classify the 5 gestures with high accuracy. This result lays the foundation for developing an FMG-based assistive device for individuals with CP.

3.3. Experimental Methods

3.3.1. Participant

The participant for this study was recruited with the help of a community physiotherapist. The inclusion criteria for participant recruitment for this study is:

- have a diagnosis of CP that limits the participant's ability to use typical commercial methods of assistive devices on/off or directional buttons/switches
- be able to follow verbal and/or visual directions

- express opinions and feedback using speech or other augmentative communication strategies.
- able to communicate in English

For this pilot study, the participant was an 18-year-old hemiplegic cerebral palsy. Hemiplegia is a common type of CP where the arm and leg on only one side (right or left) side of the body is affected [94]. About 33% of children suffer from weakness and spasticity in affected side [94]. Individuals may experience issues with arm and hand functions including: reaching, manipulating, grasping, and releasing [95]. They are often not able to plan their actions in order to complete a series of tasks related to a common goal [96].

The participant in this study was left hemiplegic and had a circumference of 17.5 cm at the forearm. Range of motion may be affected by muscle spasticity (increased resistance), so the range of motion was measured using a goniometer. Table 3 summarizes the range of motion measurements for the participant. In accordance with SFU ethics, oral and written consent was given by their legal guardian. In addition, oral and written assent was established by the participant. During the initial introductions, the participant discussed gross hand motor gestures that can be performed repeatedly without any pain or discomfort. These 5 gross motor gestures were used to complete the experimental protocol in Chapter 4.3.4.

Table 3: Range of Motion measurements taken on the affected arm of the participant

Wrist Movement	Degrees
Extension	38.0°
Flexion	30.0°
Radial	< 1.0°
Ulna	< 1.0°

3.3.2. Data Collection Devices

A custom-designed FMG band placed 8 FSRs evenly along a soft foam backing. The band was tightened around the participant's forearm using a Velcro strip. The band was tight round the limb, although still comfortable, confirmed by the user after moving their arm in an unconstrained fashion. To prevent saturation of the signal, hard-acrylic

backings (0.5 mm in width) were placed on top of each FSR using a temporary adhesive. A 16-bit microcontroller was used to sample the FSRs at 10 Hz sampling frequency. The data were relayed to a nearby laptop running a custom LabVIEW VI through the onboard Bluetooth module. Figure 3-1 shows the FMG band worn at the wrist.

During the study, the participant's arm was videotaped using a commercial high-definition webcam and was synchronized with the FMG signal to validated the labels applied by the LabVIEW VI.

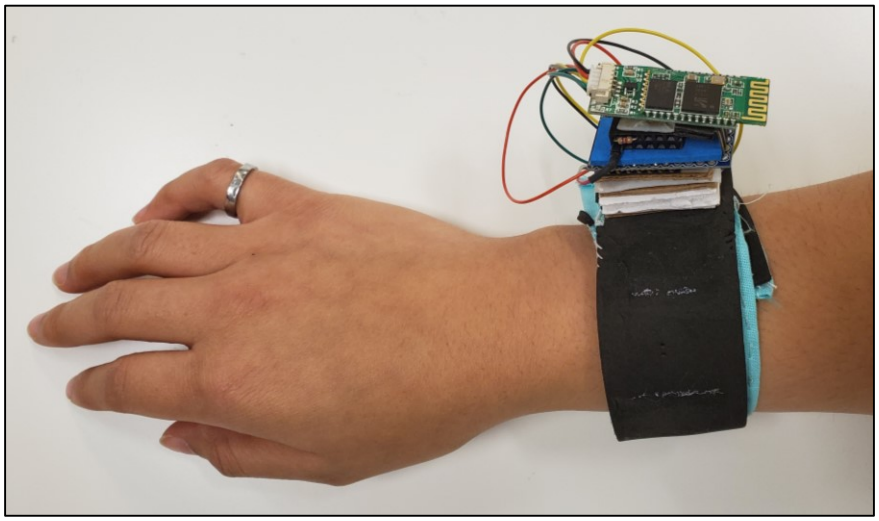

Figure 3-1: Example of the FMG band that is worn at the wrist. The FMG band has 8 embedded FSRs, a 16-bit microcontroller, and a Bluetooth module to communicate wirelessly.

3.3.3. Experimental Protocol

The participant was seated with his feet touching the ground in a comfortable chair without any armrests. The FMG band was donned on the affected left wrist. The participant would maintain a single gesture for 5 seconds and then relax. For this study the participant held the gesture for 5 seconds to ensure a stable, static signal was sampled. The order of the 5 gestures was randomized for each of the 5 trials. To mitigate the effects of muscle fatigue the participant was allowed to rest between each trial. After all trials the participant's range of motion measurement and forearm circumference measurement was taken. Figure 3-2 shows the 5 gestures performed by the observer amd Figure 3-3 shows the 5 gestures performed by the participant. The observer noted while executing the protocol the participant mirrored the gesture he

intended to do with their unaffected arm for all gestures and trials. The researchers did not ask the participant to do so nor discourage this action in any way.

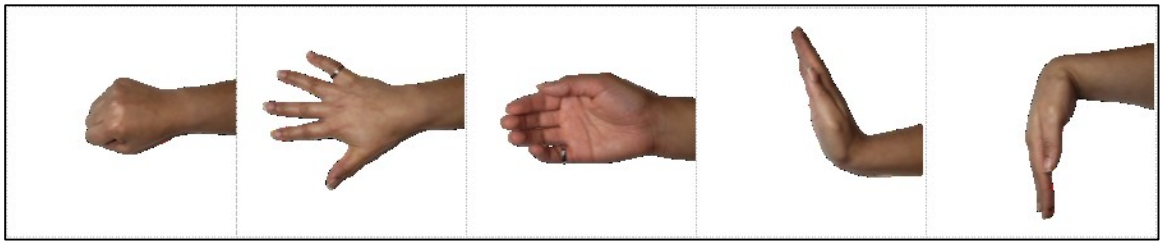

Figure 3-2: Gestures performed by the observer. 1) fist, 2) open, 3) lateral rotation, 4) extension, and 5) flexion

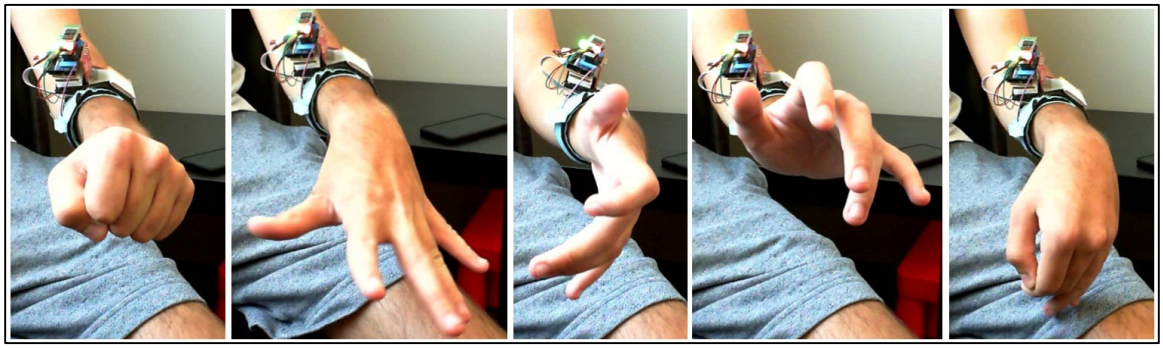

Figure 3-3: Gestures Performed by Participant. 1) fist, 2) open, 3) lateral rotation, 4) extension, and 5) flexion

3.3.4. Data Analysis

Cropping and Filtering Data

To ensure that only the stable portions of each gesture were used for classification, the first and the last seconds of the gesture were discarded. Afterwards, to remove noise and smooth out the signal, a 5th order median filter was applied. Although this step was not performed in the previous study, tremors and other motor disorders may introduce additional noise. Comparatively, the classification accuracy was higher when using the filter.

FMG Data Classification

To investigate if upper limb FMG data from a CP participant can be classified using machine learning algorithms, three classifiers were trained and tested with cross-trial evaluation. The Matlab classification learner functions, *fitdiscr*, *fitcecoc*, and *fitcknn*

were implemented for LDA, SVM and kNN respectively. For kNN the number of neighbours was set to be 1 nearest neighbour. Although hyper-parameter tuning was explored, ultimately the default values were used.

3.4. Experimental Results

3.4.1. Raw Data

Figure 3-4 provides an example of the raw FMG signal of the fist gesture from the first trial. The dotted lines in the figure denote the parts of the signal that were removed to ensure a stable signal was used for subsequent data analysis. The signal was then passed through a smoothing 5th order median filter. Figure 3-5 illustrates the FMG signal before and after filtering for all 5 gestures from a single trial.

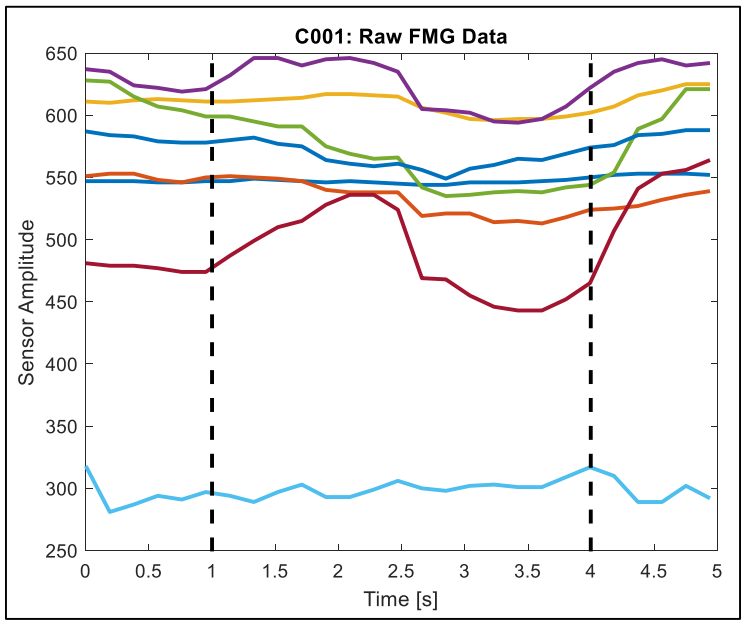

Figure 3-4: Raw FMG Data from the first trial, fist gesture. The dotted lines indicate the section of the sample that was removed.

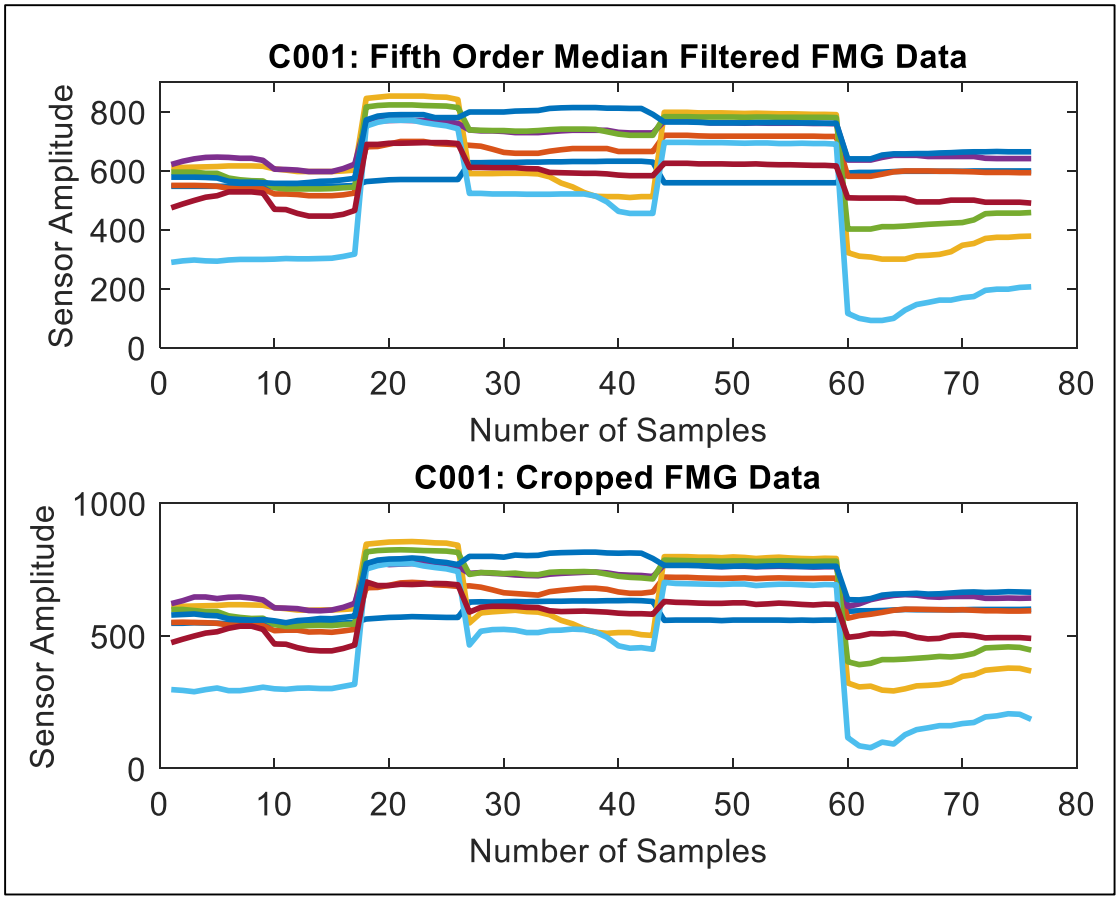

Figure 3-5: (Above) Filtered FMG data for a single trial after cropping the first and last second. (Below) The FMG data for a single trial after cropping the signal without any filtering.

3.4.2. Machine Learning Model

After filtering the data, a model was trained and tested for each of the 3 machine learning algorithms. The boxplot for the average cross-trial accuracies for LDA, SVM, and kNN are shown in Figure 3-6. The average cross-trial accuracies for LDA, SVM, and kNN were 91.0±6.4%, 93.6±5.0%, and 90.5±10% respectively. These rudimentary results show that common machine learning algorithms can be used to classify CP data with a high accuracy.

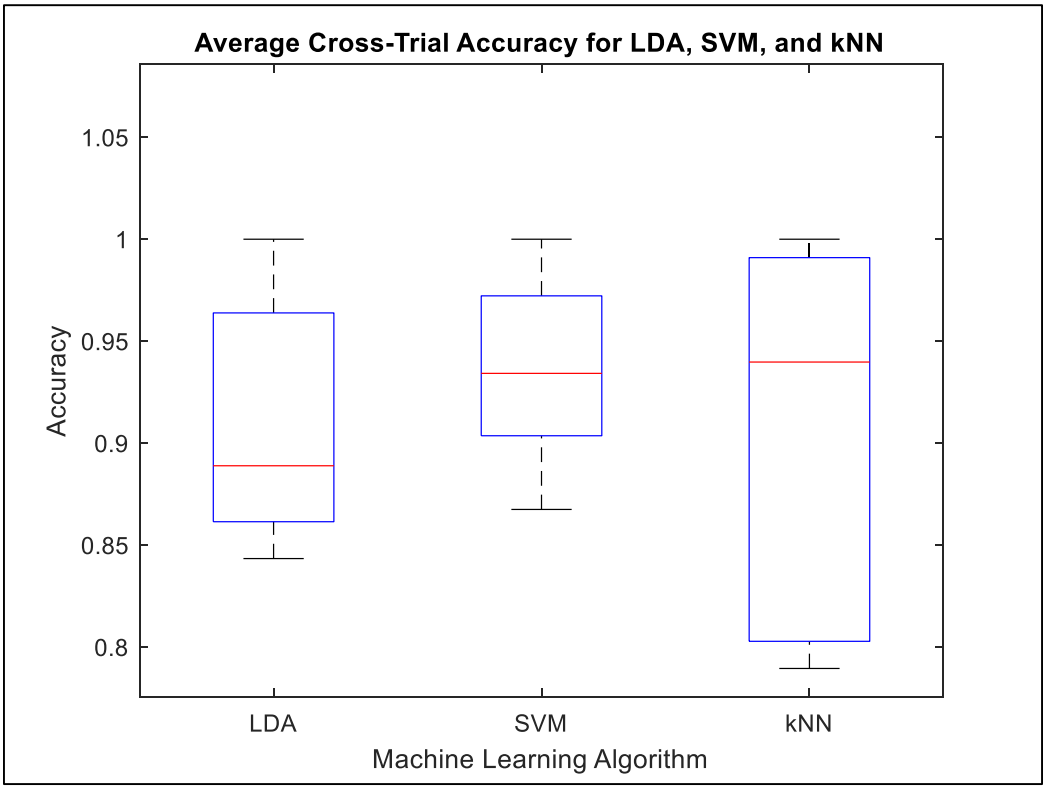

Figure 3-6: Boxplot for the cross-trial accuracies for LDA, SVM, and kNN machine learning algorithms.

3.5. Summary and Implications of Results

Individuals with CP may use assistive devices to increase their functionality and involvement in daily living. Though many studies have been done with other myosignals such as EMG and MMG [19], an inexpensive technology that has been gaining traction is FMG. FSRs can be embedded into a wearable band to acquire the FMG signal. The signal is translated into access controls using gesture recognition algorithms. This pilot study was designed to determine the feasibility of using FMG with individuals with CP. For this study, a single participant with hemiplegic CP, wore the FMG band on their affected forearm while performing 5 gestures.

Studies have shown children with hemiplegic CP tend to neglect or underuse their affected limb [70]. This is referred to as “developmental disregard”, and many rehabilitation programs try to add daily practice and use of the hemiplegic limb. However, it may be quite challenging to include. By developing an assistive the device that is used successfully with the affected limb, individuals are able to utilize their affected limb in a functional way.

Five gestures were performed by the participant in this study. Those gestures were then used to train 3 machine learning models: LDA, SVM, and kNN. All three machine learning algorithms were able to classify the 5 gestures; 1) fist, 2) extension, 3) flexion, 4) open, and 5) pronation with accuracies above 79%. In literature, a comparative study using an inertial sensing system with a single CP participant was able to train four gestures; 1) lift hand, 2) sweep hand right, 3) twist right, and 4) punch forward, with an online testing accuracy range of 60%-70% [23]. The study utilized a modified perceptron algorithm to conduct gesture recognition. A study using FMG as AT, by Delva et al. study mentioned in Chapter 2, recruited senior participants to investigate an FMG band as a smart-home controller and investigated real-time classification using LDA [41]. The model was able to classify 5 gestures with an average accuracy of 76.5% [41].

One of the concerns with assistive devices is false-negatives. There were two studies [49], [55] that looked at the reactions of participants to false negatives and user-errors in a non-clinical setting. A pilot study was done with a 9-year-old child with severe spastic quadriplegic CP [49]. The child used several single-state switches to perform activities on the computer using a vocal cord vibration switch over 2-3 sessions every 2 weeks [49]. Although the vocal cord vibration switch had shown to be a good device for the participant and had shown a great level of proficiency, the participant was impatient and intolerant of false negative errors [49]. The participant was also very cautious of making mistakes while using the vocal cord vibration switch in public [49]. In addition to mistakes causing an emotional response, another study [55] observed a physical reaction from the participants too. The study had three male spastic children between the ages of 7 and 11 who also used a vocal cord vibration switch to complete a letter matching activity, using the scanning method [55]. Of the three participants in the study, one participant was mild to moderately tense throughout the session. All three participants had strong vocalization and gross movements of the arms and head when a false negative error occurred [55]. Therefore, for an FMG-based assistive device to be successful it should be robust and highly accurate.

This study was limited by the number of participants. Since CP can manifest itself in a variety of ways, more participants would have shown the robustness' of the FMG band as an assistive device. However, obtaining ethics and recruiting for this study was very challenging and after several months, we were required to proceed with a single

participant for this study. When designing the study, we tried to limit data collection to less than 45 minutes. This was done to maintain the focus of the participant and reduce muscle fatigue. Hence, the number of gestures used in this study was limited to only 5 gestures. In future studies, the participant should be able to wear the band and make as many gestures as possible. Additionally, while wearing the band participants could perform several ADL to capture gestures that could be made inadvertently in their daily life. This could help reduce false-positives of the FMG-based assistive device. In conclusion, this study was able to show the feasibility of using FMG as an assistive device with individuals with CP.

Chapter 4. Can K-means Clustering Be Used to Perform Gesture Selection on FMG Data?

4.1. Chapter Overview

The following Chapter describes a preliminary study that tries to answer the question, can k-means clustering be used to perform gesture selection on FMG data? This study explores k-means clustering using upper-limb FMG data from healthy participants. It is intended to meet **Objective 2**; determine if k-means clustering could be implemented to lower computation time of gesture selection for FMG upper limb data. The layout of this Chapter is as follows: first an overview of the study is given, followed by experimental methods, and then experimental results. Finally, a summary of the study and the implications of the results are discussed.

4.2. Study Overview

This study was designed to investigate using k-means clustering as a method of gesture selection towards the development of a custom wearable FMG band that can interface with computers, devices, and household appliances as an assistive device. In a clinical setting, it is necessary to have quantifiable way to select gestures for a participant based on separability and reliability. The proposed method uses the popular clustering algorithm, k-means to divide the data into k clusters and then select gestures based on membership to a particular cluster. The k-means clustering method was compared to three commonly used machine learning algorithms to show reduction in computational time and compare test accuracy of the machine learning models [97].

4.3. Experimental Methods

4.3.1. Participants

Ten healthy participants between the ages of 23 and 46 were recruited from the greater community. Informed and written consent was obtained from all participants in accordance to Simon Fraser University (SFU) ethics. Although the motivation for this study were individuals with Cerebral Palsy, this preliminary study implemented an

extended protocol of ten gross motor gestures. All participants were right-hand dominant and were equally split between genders. The average participant's forearm circumference was 17.04 ± 1.5cm [97].

4.3.2. Data Collection Devices

A custom-designed wireless band was created to capture the FMG signals and is shown in Figure 4-1. The band contains 8 FSRs that were placed evenly along a soft foam backing. A hard-acrylic backing with a width of 0.5 mm was placed on top of each FSR to ensure the sensors did not bend or saturate. The band was tightened on each participant using a Velcro strip, until it was tight round the limb although comfortable for the user. A voltage divider circuit was used to connect the FSRs to a 16-bit microcontroller. The microcontroller was connected to a Bluetooth module which relayed the signal to a nearby computer running National Instruments LabVIEW VI program. LabVIEW was used to record the signal at a sampling rate of 10 Hz [97].

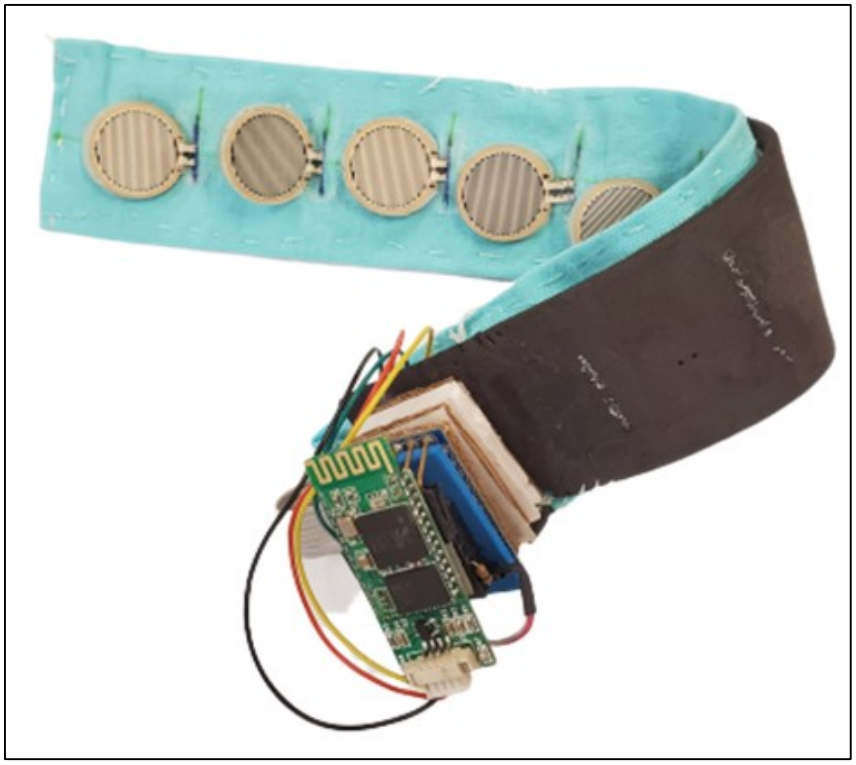

Figure 4-1: Custom designed wearable FMG band with 8 embedded FSRs, a 16-bit microcontroller and a Bluetooth module [97]

4.3.3. Experimental Protocol

Each participant wore the FMG band on the dominate-side forearm. All participants were seated comfortably with their feet touching the ground and the elbow on a hand rest, ensuring that the band and the forearm were not in contact with the hand-rest. A participant would maintain a single gesture for 3 seconds and then relax. The order of the gestures was randomized across trials and across subject. Each participant performed five trials in total. Participants were able to rest between sets as requested to mitigate the effects of muscle fatigue. As future studies will involve individuals with CP gross motor gestures that did not require fine finger dexterity or fine motor skills were selected and are presented in Figure 4-2. These hand gestures are commonly used in daily life and rehabilitation exercises [42] [97]. The gestures were; A) rest, B) open, C) thumb up, D) fist, E) flexion, F) extension, G) radial, H) ulna, I) pronation and J) supination.

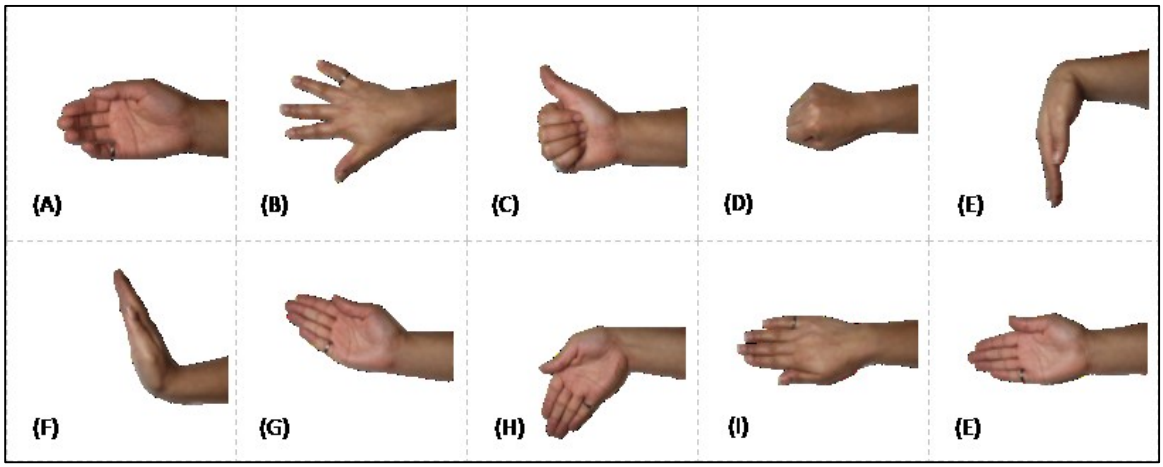

Figure 4-2: Gestures performed by all participants. Each gesture was held for 3 seconds and was randomized between sets and participants [97].

4.3.4. Data Analysis

The raw collected data were processed and analyzed with a custom-written Matlab script**.** High-frequency and smoothing filters were investigated, however in the end the raw data was used. For each participant, two gesture selection methods were implemented to determine the best gestures for 2 to 9 classes, out of the 10 total gestures.

The first algorithm utilized k-means clustering to find the selected gestures. The data were clustered using the Matlab k-means function *kmeans* into *k* clusters. This function was set to minimize the squared Euclidean distance between one observation and the mean of the points in that cluster. Equation (9) [45] gives the squared Euclidean distance where x_i represents the ith data sample and c_i represents the ith centroid location. The *replicates* feature was set to 10, repeating the clustering process 10 times to ensure the solution has the minimum squared Euclidean distance. Then, for each cluster, the gestures with the most samples belonging to that particular cluster were chosen as the selected gestures [97]. Figure 4-3 outlines the steps to select a sub-set of gestures using the k-means clustering method.

$$J = \sum_{i=1}^{N} \left(\underset{j}{argmin} ||x_i - c_i||_2^2 \right) [45] \tag{9}$$

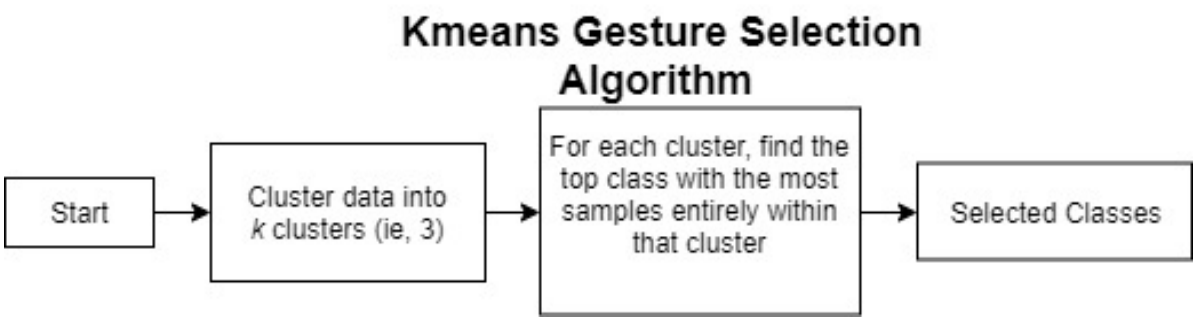

Figure 4-3: Flowchart outlining the k-means gestures selection method proposed in this Thesis [97].

To compare the k-means clustering method of gesture selection, three machine learning algorithms were implemented; 1) LDA, 2) SVM, and 3) KNN. To find the *k* best gestures out of the 10 gestures, all possible combinations of k gestures was found using the Matlab function, *nchoosek*. Table 4 shows the number of combinations possible with 10 total gestures for a given k value. For every combination of gestures found, the selected data were used to train a model for each of the machine learning algorithms, and a cross-trial evaluation was performed. The *k* best gestures were determined to be the gestures that gave the highest average cross-trial accuracy [97].

Table 4: The number of combination of gestures possible for a given number of classes

Number of Classes	Number of Different Gesture Combinations Possible
2	45
3	120
4	210
5	252
6	210
7	120
8	45
9	10

The k-means clustering gesture selection method and the machine learning gesture selection method were compared to each other on cross-trial classification accuracy and computational time. A statistical analysis was done to determine if there is a significant difference between the algorithm accuracy means.

4.4. Experimental Results

4.4.1. Classification Accuracy for K-Means Clustering Method

For the k-means method, as described in Figure 4-3, the selected gestures were chosen based on the number of samples from a labelled gesture that were members of a particular cluster. After determining the selected gestures, the data were used to train three machine learning models: LDA, SVM, and KNN. The average accuracy across all participants and classes was 95.9 ± 4%, 94.7 ± 4%, 96.2 ± 3%, for LDA, SVM, and kNN, respectively. Table 6 shows the cross-trial accuracies for all three machine learning models for the selected gestures for a given number of classes for all participants.

Table 5: Average cross-trial accuracies for LDA, SVM, and kNN for each participant for k-means clustering method of gesture selection.

	Participant 1				Participant 6		
k	LDA + k-means	SVM + k-means	kNN + k-means	k	LDA + k-means	SVM + k-means	kNN + k-means
2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
5	0.96 ± 0.09	0.95 ± 0.09	0.94 ± 0.09	5	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
6	0.96 ± 0.07	0.95 ± 0.07	0.95 ± 0.07	6	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
7	0.91 ± 0.09	0.95 ± 0.04	0.94 ± 0.07	7	1.00 ± 0.00	1.00 ± 0.01	1.00 ± 0.00
8	0.89 ± 0.06	0.90 ± 0.03	0.91 ± 0.06	8	1.00 ± 0.00	0.99 ± 0.01	1.00 ± 0.00
9	0.90 ± 0.04	0.92 ± 0.02	0.92 ± 0.05	9	0.94 ± 0.07	0.95 ± 0.05	0.98 ± 0.03

	Participant 2				Participant 7		
k	LDA + k-means	SVM + k-means	kNN + k-means	k	LDA + k-means	SVM + k-means	kNN + k-means
2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	2	0.94 ± 0.14	1.00 ± 0.00	1.00 ± 0.00
3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
5	1.00 ± 0.00	1.00 ± 0.01	1.00 ± 0.00	5	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
6	1.00 ± 0.00	1.00 ± 0.01	1.00 ± 0.00	6	0.95 ± 0.10	0.99 ± 0.02	1.00 ± 0.01
7	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	7	0.97 ± 0.07	0.97 ± 0.05	0.97 ± 0.03
8	1.00 ± 0.01	1.00 ± 0.00	1.00 ± 0.00	8	0.97 ± 0.06	0.96 ± 0.06	0.99 ± 0.02
9	0.97 ± 0.05	0.99 ± 0.03	0.98 ± 0.05	9	0.94 ± 0.05	0.97 ± 0.05	0.99 ± 0.02

	Participant 3				Participant 8		
k	LDA + k-means	SVM + k-means	kNN + k-means	k	LDA + k-means	SVM + k-means	kNN + k-means
2	0.97 ± 0.06	1.00 ± 0.00	1.00 ± 0.00	2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
3	0.97 ± 0.05	0.99 ± 0.02	0.99 ± 0.02	3	0.99 ± 0.02	1.00 ± 0.00	0.99 ± 0.02
4	0.97 ± 0.06	0.99 ± 0.02	0.99 ± 0.01	4	0.96 ± 0.06	0.96 ± 0.08	0.93 ± 0.12
5	0.99 ± 0.01	0.96 ± 0.09	1.00 ± 0.00	5	0.97 ± 0.04	0.97 ± 0.05	0.95 ± 0.09
6	0.97 ± 0.04	0.96 ± 0.07	0.98 ± 0.03	6	0.97 ± 0.06	0.96 ± 0.05	0.94 ± 0.08
7	0.94 ± 0.09	0.95 ± 0.06	0.98 ± 0.03	7	0.94 ± 0.08	0.92 ± 0.12	0.93 ± 0.10
8	0.96 ± 0.05	0.91 ± 0.05	0.95 ± 0.04	8	0.95 ± 0.07	0.93 ± 0.10	0.94 ± 0.09
9	0.90 ± 0.09	0.80 ± 0.05	0.86 ± 0.04	9	0.94 ± 0.09	0.93 ± 0.10	0.93 ± 0.09

k	Participant 4			k	Participant 9		
	LDA + k-means	SVM + k-means	kNN + k-means		LDA + k-means	SVM + k-means	kNN + k-means
2	0.97 ± 0.06	0.96 ± 0.09	0.96 ± 0.08	2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
3	0.94 ± 0.10	0.95 ± 0.10	0.98 ± 0.05	3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
4	0.98 ± 0.03	0.97 ± 0.05	1.00 ± 0.01	4	0.96 ± 0.10	1.00 ± 0.00	1.00 ± 0.00
5	0.86 ± 0.13	0.92 ± 0.11	0.90 ± 0.10	5	0.95 ± 0.09	0.80 ± 0.14	0.94 ± 0.08
6	0.90 ± 0.10	0.92 ± 0.10	0.89 ± 0.11	6	0.96 ± 0.07	0.77 ± 0.15	0.92 ± 0.07
7	0.84 ± 0.11	0.84 ± 0.10	0.84 ± 0.12	7	0.95 ± 0.06	0.77 ± 0.16	0.92 ± 0.05
8	0.85 ± 0.09	0.81 ± 0.13	0.72 ± 0.10	8	0.90 ± 0.10	0.89 ± 0.10	0.95 ± 0.05
9	0.83 ± 0.11	0.81 ± 0.15	0.73 ± 0.07	9	0.91 ± 0.09	0.91 ± 0.09	0.92 ± 0.14

k	Participant 5			k	Participant 10		
	LDA + k-means	SVM + k-means	kNN + k-means		LDA + k-means	SVM + k-means	kNN + k-means
2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	3	1.00 ± 0.00	0.99 ± 0.01	0.99 ± 0.01
4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	4	0.99 ± 0.01	0.94 ± 0.07	0.99 ± 0.01
5	1.00 ± 0.00	0.98 ± 0.05	1.00 ± 0.00	5	0.97 ± 0.02	0.94 ± 0.06	0.98 ± 0.02
6	0.95 ± 0.07	0.94 ± 0.12	0.97 ± 0.05	6	0.97 ± 0.02	0.94 ± 0.05	0.98 ± 0.01
7	0.94 ± 0.08	0.95 ± 0.08	0.97 ± 0.04	7	0.96 ± 0.06	0.93 ± 0.07	0.97 ± 0.01
8	0.92 ± 0.09	0.94 ± 0.09	0.96 ± 0.07	8	0.95 ± 0.05	0.91 ± 0.05	0.95 ± 0.03
9	0.85 ± 0.10	0.92 ± 0.08	0.94 ± 0.07	9	0.91 ± 0.07	0.84 ± 0.10	0.90 ± 0.06

4.4.2. Classification Accuracy for Machine Learning Models

To compare the accuracy and feasibility of the proposed k-means method of gesture selection, three widely used machine learning algorithms were used to train models with every possible combination of gestures for a given number of classes. The maximum average cross-trial accuracy for a given number of classes were deemed the best gestures. The average accuracy across all participants and classes for LDA, SVM, and kNN were 98.3 ± 2%, 97.7 ± 2%, and 98.1 ± 0.00%, respectively. The average cross-trial accuracies for the LDA, SVM and KNN models for the all participants are given in Table 6.

Table 6: Average cross-trial accuracies for LDA, SVM, and kNN for each

	Participant 1				Participant 6		
k	**LDA**	**SVM**	**kNN**	*k*	**LDA**	**SVM**	**kNN**
2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
5	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	5	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
6	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	6	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
7	1.00 ± 0.00	1.00 ± 0.01	0.99 ± 0.02	7	1.00 ± 0.00	1.00 ± 0.01	1.00 ± 0.00
8	0.98 ± 0.04	0.95 ± 0.05	0.95 ± 0.05	8	0.97 ± 0.06	0.95 ± 0.04	0.97 ± 0.04
9	0.93 ± 0.06	0.92 ± 0.04	0.91 ± 0.04	9	0.93 ± 0.06	0.92 ± 0.07	0.95 ± 0.05

	Participant 2				Participant 7		
k	**LDA**	**SVM**	**kNN**	*k*	**LDA**	**SVM**	**kNN**
2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
5	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	5	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
6	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	6	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
7	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	7	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
8	1.00 ± 0.01	1.00 ± 0.00	1.00 ± 0.00	8	1.00 ± 0.01	0.99 ± 0.01	1.00 ± 0.00
9	0.98 ± 0.02	0.99 ± 0.03	0.98 ± 0.02	9	0.97 ± 0.05	0.97 ± 0.05	0.99 ± 0.02

	Participant 3				Participant 8		
k	**LDA**	**SVM**	**kNN**	*k*	**LDA**	**SVM**	**kNN**
2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
5	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	5	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
6	0.99 ± 0.01	0.99 ± 0.01	1.00 ± 0.00	6	1.00 ± 0.00	1.00 ± 0.00	0.98 ± 0.04
7	0.97 ± 0.05	0.96 ± 0.06	0.98 ± 0.02	7	1.00 ± 0.01	0.97 ± 0.06	0.97 ± 0.04
8	0.96 ± 0.05	0.92 ± 0.07	0.96 ± 0.04	8	0.98 ± 0.04	0.95 ± 0.05	0.94 ± 0.09
9	0.90 ± 0.09	0.86 ± 0.15	0.94 ± 0.04	9	0.92 ± 0.07	0.92 ± 0.08	0.91 ± 0.09

	Participant 4				Participant 9		
k	**LDA**	**SVM**	**kNN**	*k*	**LDA**	**SVM**	**kNN**
2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
5	1.00 ± 0.01	1.00 ± 0.00	1.00 ± 0.00	5	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
6	0.98 ± 0.04	0.97 ± 0.04	0.99 ± 0.01	6	0.99 ± 0.02	0.97 ± 0.03	1.00 ± 0.00
7	0.96 ± 0.08	0.94 ± 0.07	0.92 ± 0.09	7	0.96 ± 0.05	0.96 ± 0.06	0.98 ± 0.04
8	0.91 ± 0.10	0.88 ± 0.11	0.86 ± 0.09	8	0.94 ± 0.04	0.94 ± 0.06	0.95 ± 0.06
9	0.83 ± 0.11	0.81 ± 0.18	0.73 ± 0.07	9	0.91 ± 0.10	0.90 ± 0.08	0.93 ± 0.09

	Participant 5				Participant 10		
k	**LDA**	**SVM**	**kNN**	*k*	**LDA**	**SVM**	**kNN**
2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	2	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00
3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	3	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.01
4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	4	1.00 ± 0.00	0.99 ± 0.01	0.99 ± 0.01
5	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	5	0.99 ± 0.01	0.99 ± 0.01	0.98 ± 0.01
6	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	6	0.99 ± 0.01	0.97 ± 0.02	0.98 ± 0.01
7	1.00 ± 0.00	0.99 ± 0.02	1.00 ± 0.00	7	0.98 ± 0.02	0.94 ± 0.04	0.98 ± 0.01
8	0.96 ± 0.06	0.97 ± 0.05	0.97 ± 0.04	8	0.96 ± 0.02	0.91 ± 0.05	0.96 ± 0.02
9	0.90 ± 0.08	0.94 ± 0.06	0.95 ± 0.04	9	0.93 ± 0.03	0.86 ± 0.08	0.94 ± 0.02

A two-way ANOVA statistical test was performed to compare each k-means cross-trial accuracy with the machine learning method accuracy. The average accuracy means for each class across all participants were compared for each method option: 1) k-means followed by LDA, 2) k-means followed by SVM, and 3) k-means followed by kNN and then only 4) LDA, 5) SVM and 6) kNN. After conducting the ANOVA test, the Tukey Range Test to compare the means was performed and Figure 4-4 shows the average means for the 6 method. The results were that there was no statistical difference between all 6 method options [97].

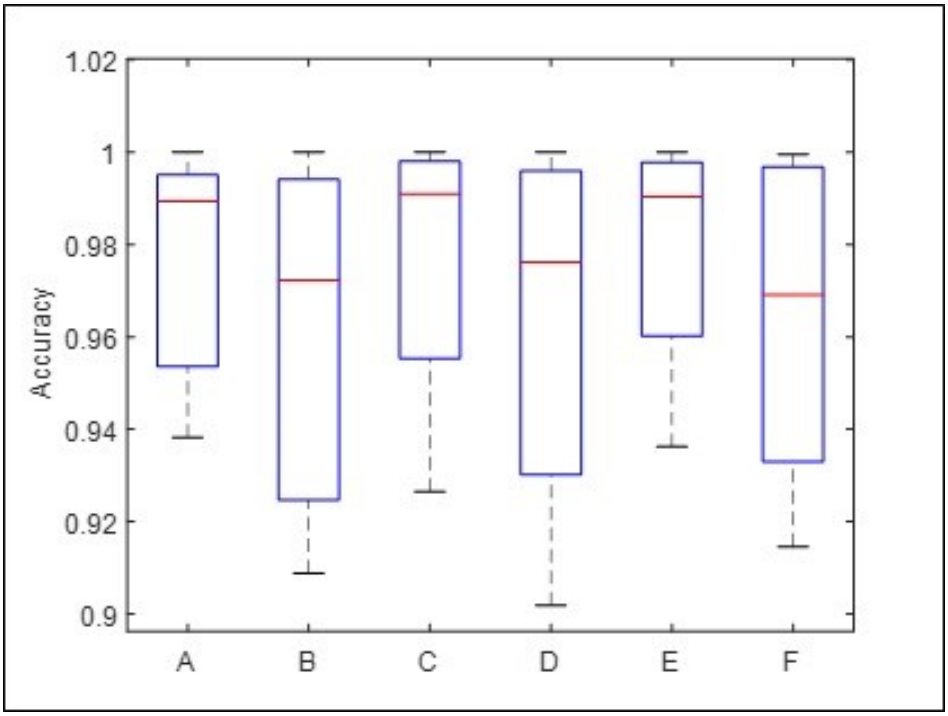

Figure 4-4: Average cross-trial validation accuracy across all participants, for all three machine learning algorithms. A = LDA, B = SVM, C = kNN, D = K-means + LDA, E = K-means + SVM, F = K-means + kNN [97]

4.4.3. Computational Time Comparison

One of the main benefits of applying the k-means method for gesture selection is its relatively low computational time. In a clinical setting, a therapist should to be able to identify reliable and a separable set of gestures, train the band and the educated the user with the FMG band in a single appointment. Therefore, being able to determine suitable gestures within a short period of time is crucial. To calculate the computation time, the timer function was implemented in Matlab. For the k-means clustering method of gesture selection the time required to cluster the data was added to the time needed to train and test a classifier. For the machine learning method, the time required to train and testing the machine learning classifier for all possible combinations of gestures for a given k value was recorded. The comparison between both methods for LDA, SVM, and kNN are shown in Figure 4-5, Figure 4-6, and Figure 4-7 respectively. Based on these results using the k-means clustering to find the best gestures, the computational time is observably faster.

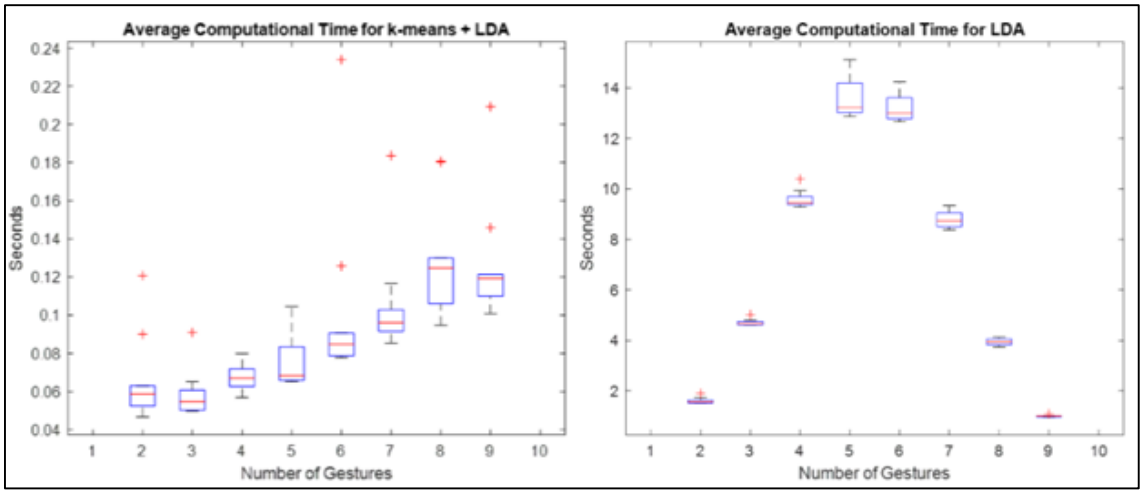

Figure 4-5: Average computation time across all participants for each number of selected gestures. Left is the k-means method of gesture selection and then classified with LDA, right is only LDA.

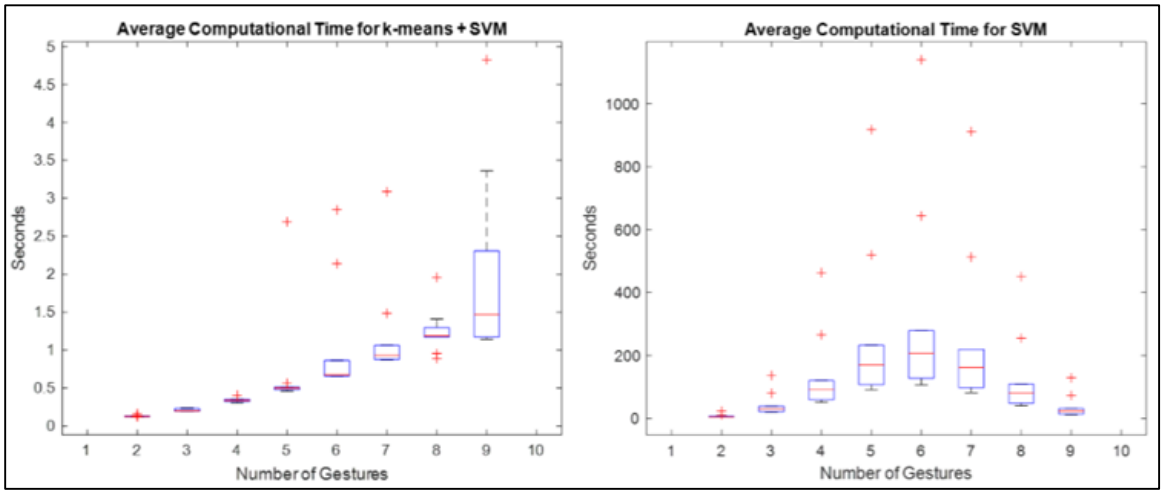

Figure 4-6: Average computation time across all participants for each number of selected gestures. Left is the k-means method of gesture selection and then classified with SVM, right is only SVM.

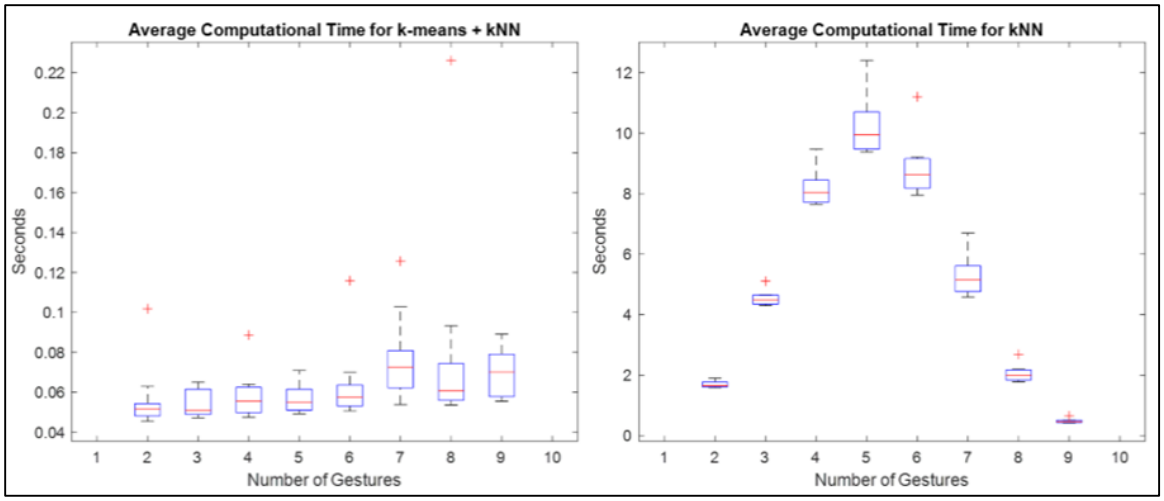

Figure 4-7: Average Computation Time across all participants for each number of selected gestures. Left is the k-means method of gesture selection and then classified with kNN, right is only kNN.

4.5. Summary and Implications of Results

Individuals with CP use assistive devices to increase their independence and gain functionality that can be hindered by physical disturbances such as spasticity, dystonia, or decreased muscle tone. Using gesture recognition, wearable devices can be used as an interface between an intended action and the peripheral device. However, in a clinical setting therapists need a way to determine which gestures should be used as an access control for an FMG-based wearable device quickly.

This study explored the use of k-means clustering to answer the research question presented in the motivation of this Thesis: Can k-means clustering be used to lower computational time of class selection for FMG upper limb data? The results of this study were able to show that the k-means clustering method is able to output the ideal gesture subset for a given participant faster than training machine learning models with all the possible gesture combinations for a given number of classes. In this study only 10 gestures were considered. This is because of the time it would take to train and test additional models for the machine learning method. For this study, using 10 gestures, a total of 5,060 models were trained and tested with cross-trial evaluation. To add more gestures would have meant the data analysis would have taken considerably longer. However, since k-means method of gesture selection only needs to train one model more gestures can be used for selection.

For this study the average cross-trial accuracy for the k-means method was 95.9 ± 4%, 94.7 ± 4%, and 96.2 ± 3% for LDA, SVM, and kNN respectively. The statistical analysis was able to show there is no statistical difference between the accuracy means of the two methods: k-means and machine learning. This results are also comparable to machine learning accuracies found in literature for FMG data. A study done by Jiang et al. [42] used 48 fine finger movements and words from the ASL. The average cross-trial accuracy for healthy participants while wearing the FMG band on their forearm with 8 FSRs was 83.5±5.6% [42]. Although this study only had 8 FSRs and used the raw FMG data, other FMG studies have used +16 sensors and included feature extraction, root-mean-squares (RMS), standard deviation, and FSR magnitudes [74]. Future work needs to be done on higher dimensional FMG data possibly with an adapted k-means algorithm since it performs well with lower dimensional data. This is due to algorithm's assumption of the data's convex shape.

Using k-means clustering to conduct gesture selection on FMG data could have the potential to help therapists determine ideal gestures that are comfortable for each individual and will provide a high level of reliability for the wearer of the FMG band. In future studies individuals with CP can wear the FMG band while doing ADL or moving freely to allow researchers to collect unconstrained data. This will prevent gestures that are not distinguishable from other actions of daily life from being chosen, limiting false negatives. Furthermore, silhouette plots described in Chapter 2.4.4 could be utilized to find the ideal number of gestures for a user at a given FMG band location. This is beneficial since classification algorithms cannot provide this information. Although, additional research is necessary, this exploratory study was able to use k-means clustering to perform gestures selection on upper limb FMG data with a high accuracy and a lower computational time. The results from this study may be used towards the development of a FMG assistive device for populations with motor disorders, such as CP.

Chapter 5. K-means Gesture Selection with Cerebral Palsy Participants

5.1. Chapter Overview

This Chapter is intended to meet **Objective 3;** using k-means with upper limb FMG data from participants with CP. The results and implications of applying the k-means gesture selection method to upper limb FMG data from an individual with CP are detailed. The data was collected during the pilot study presented in Chapter 3. There were 5 gross motor gestures and each gesture had 5 repetitions. The data analysis is described, followed by the results, and the implications.

5.2. Dataset

The data from the pilot study in Chapter 3.3.3 was used to implement gesture selection. The participant performed 5 static gestures for 5 seconds with 5 trials. Figure 3-3 shows the participant performing the 5 gestures: 1) fist, 2) open, 3) lateral rotation, 4) extension, and 5) flexion.

To ensure the signal is stable the data was cropped. Then the data was filtered with a 5th order median filter to smooth out the signal. The pre-processing applied to the dataset is described in detail in Chapter 3.3.4.

5.3. Data Analysis

Both methods described in Chapter 4.3.4, k-means clustering and machine learning, were implemented to find the best gestures for 2 to 4 classes, out of the 5 total gestures. The k-means method clustered the given gestures into k clusters and for each cluster the class with most samples that belonged to that particular cluster were selected as the *k* best gestures. Those gestures were used to train and perform cross-trial evaluation using LDA, SVM and kNN classifier models. The total time needed to cluster the data into k clusters, train and test the model were noted.

The machine learning method found all possible combinations of gestures for a given k and used those gestures to train and test a classifier. Three classifiers were

implemented: LDA, SVM and kNN. The time it took to classifier all possible combinations of gestures was noted to compare it to the k-means method.

5.4. Results

Accuracy

The cross trial accuracies for using the k-means clustering for gesture selection were calculated. The average accuracies for 2 classes were 100±0%,100±0%, and 100±0% for LDA, SVM, and kNN respectively. For 3 classes 100±0%,100±0%, and 98.40±3.6% for LDA, SVM, and kNN respectively and finally for 4 classes 100±0%,100±0%, and 98.20±3.2% for LDA, SVM, and kNN.

The cross trial accuracies for the exhaustive machine learning gesture selection method also calculated, the average accuracies for 2 classes were 100±0%,100±0%, and 100±0% for LDA, SVM, and kNN. For 3 classes 100±0%,100±0%, and 100±0% for LDA, SVM, and kNN and finally for 4 classes 99.62±0.86%, 99.63±0.84%, and 97.18±3.13% for LDA, SVM, and kNN respectively.

Computational Time Comparison

The computation time comparison is shown graphically in Figure 5-1. Even for a smaller subset of classes compared to the previous study in Chapter 4 the k-means method is observably faster than all the machine learning methods. Taking the complexities of the different algorithms into consideration, the results follow expectations that SVM took considerably longer than LDA, kNN and k-means. In a clinical setting, the k-means method will allow clinicians and researchers to quickly conduct gesture selection on all possible muscle movements, gestures, and sign languages.

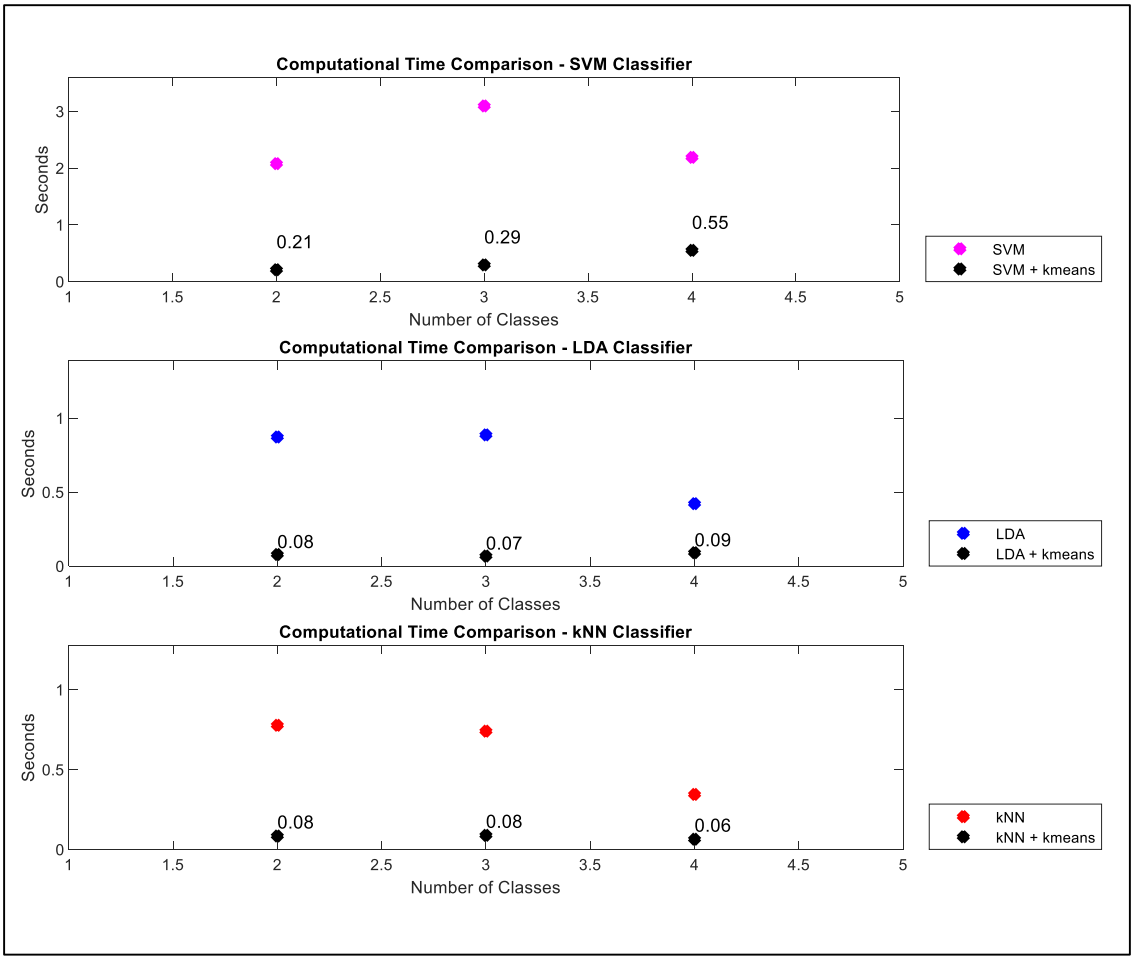

Figure 5-1: Computation time comparison for all three machine learning classifiers. The k-means method is labelled to show the exact value.

5.5. Summary and Implication of Results

FMG data collected from a participant with CP was used to implemented gesture selection using k-means clustering. The cross-trial accuracies after k-means clustering for each classifier model was in the accuracy range of 98% - 100% for LDA, SVM and kNN algorithms. After finding all possible combinations of classes and the subsets with the highest accuracy the accuracy range for those gestures was 97% - 100% for all three algorithms. Using the k-means gesture selection method therapists and researchers can quickly identify selected gestures from a larger set of initial gestures. Additionally, the silhouette plots can be constructed to find the ideal number of gestures for a participant at a given FMG band location. However, the main advantage of the k-means clustering method, is the computation time. This study found the computation

time for performing k-means clustering was observably faster than selecting gestures using machine learning. These results are also comparable to the results found with the healthy participants in Chapter 4. The initial study had a limit on the length of time it took to collect the data, so only 5 gestures were collected. However, as the number of gestures increase the more benefit there is to applying the k-means method of gesture selection. Future studies can incorporate more participants to capture more forms of CP.

In summary this work was able to implement k-means method of gesture selection to FMG data from an individual with CP. The results of the k-means method had a high classification accuracy across all classifiers and faster computational time.

Chapter 6. Application of k-Means Gesture Selection

6.1. Chapter Overview

To develop an experimental study with CP participants to evaluate the gestures selection k-means method, as well as the FMG band, preliminary work was completed as part of this Thesis. The following Chapter explores one application of using an FMG band and gesture selection using k-means method with healthy participants. In the beginning, different possible research strategies are discussed, followed by experimental methods, and then initial results. Finally, a summary and implications for future studies are presented.

6.2. Experimental Strategies

Various strategies to test the application of the FMG band were evaluated and constructed. As many literary sources concluded, adoption of assistive technologies in childhood is the key to successful integration in daily life. Hence, all strategies were designed with child's attention span, interests, and varying capabilities in mind. After meetings with therapists from the community, it was observed that children used battery operated toys that had been altered with a 3.5 mm mono audio jack in order to use an assistive mechanical switch instead of the smaller buttons or remote controls that came with the toy. Figure 6-1 provides examples of toys that were altered with female audio jack. Additionally, many toys made noises or had flashing lights to keep the child's attention.

Figure 6-1: Examples of toys altered with an AUX to insert single state switches or a Bluetooth switch

Many toys and technologies were considered, such as augmenting a remote controlled car with a Bluetooth switch that can be controlled with gestures performed by a user while wearing the FMG band. A Bluetooth module and a 16-bit microcontroller were designed with a simple bipolar junction transistor (BJT) switch circuitry to receive signals from a Labview VI that was classifying FMG signals into command gestures. Figure 6-2 shows the encased Bluetooth switch on the augmented toy train. However, this option was not very flexible and other features like speed, lights, and sound of the toy were not controllable. Furthermore, since some toys could move freely in a 2D plane, a participant may steer the car in the wrong direction or have difficulty judging the speed of the car, for example when to stop or turn the car. Subsequently, a line-following toy robot was chosen to follow a path drawn on a poster board.

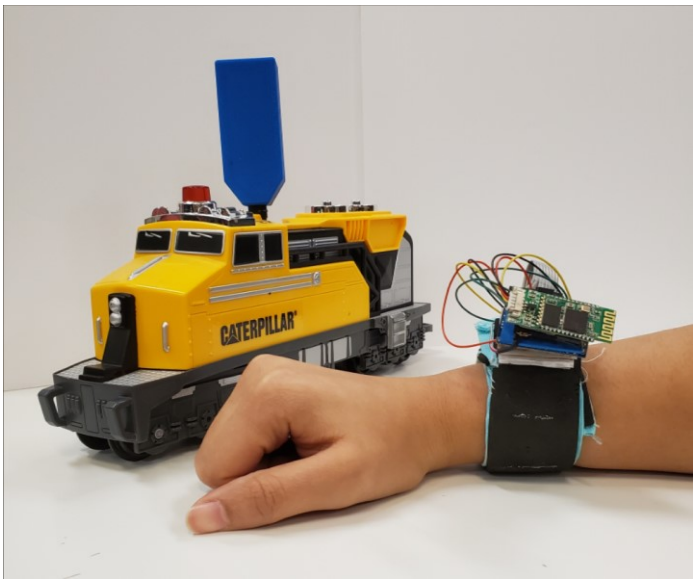

Figure 6-2: Bluetooth receiving switch connected with a mono audio jack

6.3. System Design

A toy robot, called Vortex by DF Robots, was selected. The Vortex is an open-source Arduino-based robot with a low energy Bluetooth (BLE) module on board and a compatible open-source Android app. It can also play music files and has several programmable LEDs. The 4 wheels are controlled with 4 motors that may be programmed to different speeds and directions. It is controlled through the Android app.

Figure 6-3: Vortex Robot, LEDs lights on

For this initial research, the robot was programed to follow a set path had been drawn on a white poster board. Figure 6-4 shows the path that was created with black paint. The Vortex robot has 7 optical sensors on the bottom and can detect markings along the path. The Vortex was programmed to pause every time it encounters a dot along the path. Depending if the dot was on the right or the left of the path, a different control command (gesture) was necessary to put the Vortex robot back in motion. In addition, the Vortex would turn red or blue to indicate which gesture was needed. An Android app was built to communicate between the Vortex robot and the laptop running a LabVIEW VI. The LabVIEW VI would send a predicted gesture to the tablet and the tablet would relay the gesture command to the Vortex robot. The following sections detail the experimental methods and results from this initial study using the Vortex robot with healthy participants.

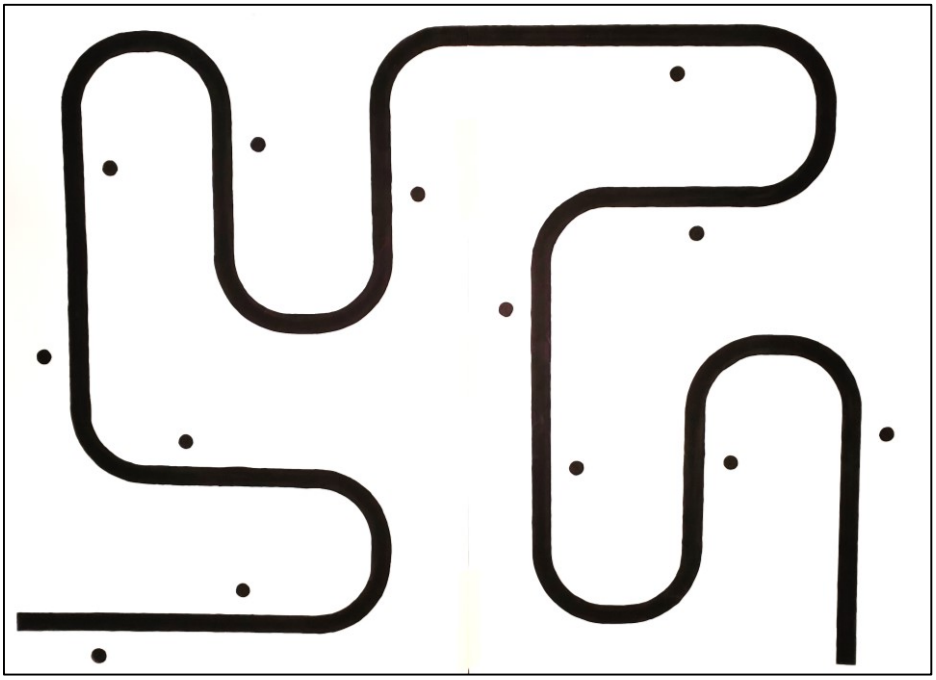

Figure 6-4: Path drawn on a whiteboard for the Vortex robot to follow. The dots indicated locations were the participants had to perform a gesture before the Vortex robot continued on the path.

6.4. Experimental Methods

6.4.1. Participants

Three healthy participants between the ages of 24 and 26 were recruited from Menrva Research lab. Informed and written consent was obtained, with accordance to Simon Fraser University (SFU) ethics. As this was preliminary research an extended protocol with healthy participants was implemented.

6.4.2. Data Collection Devices

The 8-FSR custom FMG band from Chapter 3 and 4 utilized for this study. Figure 4-1 shows the FMG band worn on the wrist. The FMG band has a 16-bit microcontroller that was used to sample the FSRs at a 10 Hz sampling frequency. All the data were relayed to a nearby laptop running a custom LabVIEW VI through the onboard Bluetooth module.

To evaluate the online classification accuracy, the participant's arm with the FMG band and the Vortex robot following the path was videotaped using a commercial high-definition webcam. The video was synchronized with the FMG band samples to manually apply ground truth labels after each session. The ground truth labels are necessary to validate the accuracy of the model after online testing.

6.4.3. Experimental Protocol

The participants wore the FMG band on their dominant forearm while comfortably seated with their feet touching the ground, ensuring that their arm and the FMG band was not in contact with the chair's armrest. The data collection was split into three sections; 1) gesture selection, 2) training, and 3) online testing. For the gesture selection, each participant performed 12 gestures for 3 seconds over 3 trials. The 12 gestures were randomized for each of the 3 trials, across all participants. Participants were not corrected if they changed the gesture slightly (ie. Thumb up during point vs thumb down during point), the observed did remind them to make subsequent gestures the same way. Figure 6-5 shows the 12 gestures performed by each participant. After

performing gesture selection using k-means clustering, the top 3 gestures were re-collected over 3 trials and that was used to train an LDA machine learning model.

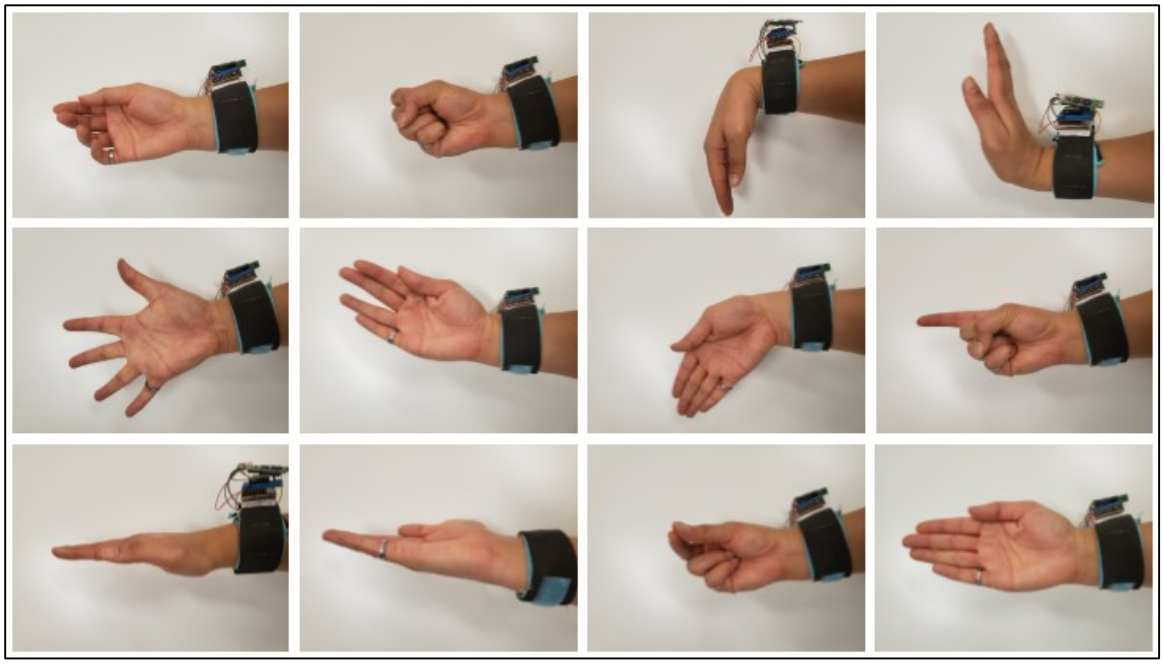

Figure 6-5: 12 Gestures performed for gesture selection

For online classification, the participants were instructed to perform one of two gestures when the Vortex stopped and turned blue, and the other gesture when the Vortex stopped and turned red. While the Vortex was moving they were to remain in "rest" position. They were instructed that the task would not be judged based on time, however the total time was recorded.

6.4.4. Data Analysis

To perform gesture selection, the FMG data of the 12 gestures was clustered into 3 clusters and the 3 gestures that had the most samples belonging to a single cluster were chosen. This was the same algorithm presented in Chapter 4.3.4. If there were multiple gestures with an equally high percentage of samples belonging to the same cluster, the gestures were picked based on a user's comfort.

After choosing the three gestures, the most comfortable gesture was "rest" while the other two gestures were mapped to "right" and "left" commands. The training samples for those three gestures were used to classify an LDA model using Matlab's

LDA function *fitdiscr*. Then, that model was used to classify samples online. The LabVIEW VI was able to use Matlab's prediction function *predict* to classify samples in real-time. The predicted gesture would be mapped to a command that was sent through a Transmission Control Protocol (TCP) connection to Samsung Galaxy Tab A tablet running the custom-built Android App. The App would communicate the command via Bluetooth to the Vortex to set it back into motion.

6.5. Experimental Results

6.5.1. K-means Clustering Gesture Selection

After clustering the data into three clusters, the top gestures for each participant were found. Table 7 shows the gestures chosen for the three controls for each participant.

Table 7: Gestures Selected for each Participant

	Rest	Gesture 2 (red)	Gesture (blue)
Participant 1	Neutral	Extension	Fist
Participant 2	Fist	Open	Point
Participant 3	Neutral	Point	Radial

6.5.2. Training and Online Testing

After re-collecting 3 trials of data for the top gestures, the average training accuracy across the 3 participants was 98.0±1.44%, Table 8 shows the training accuracy for the three participants.

Table 8: Training accuracy for all participants

	Training Accuracy
Participant 1	97.22%
Participant 2	97.16%
Participant 3	99.68%
Average	98.0±1.44%

For the online testing, the Vortex was set to travel around the path and was synchronized to start moving when the recording of each online testing session started. The average accuracy across the 3 participants was 81.9±5.28%. the online testing accuracy for all 3 participants is shown in Table 9. Figure 6-6 shows the predicted gestures over time for all 3 participants with incorrectly classified samples marked with a red “x” and correctly classified samples marked with a blue circle. When a participant was transitioning between two gestures the time was recorded and it is presented in the figure as well. In a longer study where few trials of online testing are performed, the reaction time of participants can be compared over time. On average it took participants 100.8 ± 6.26 seconds to complete the full track.

Table 9: Online testing accuracy for all participants

	Online Testing Accuracy
Participant 1	80.00%
Participant 2	77.99%
Participant 3	87.99%
Average	81.9±5.28%

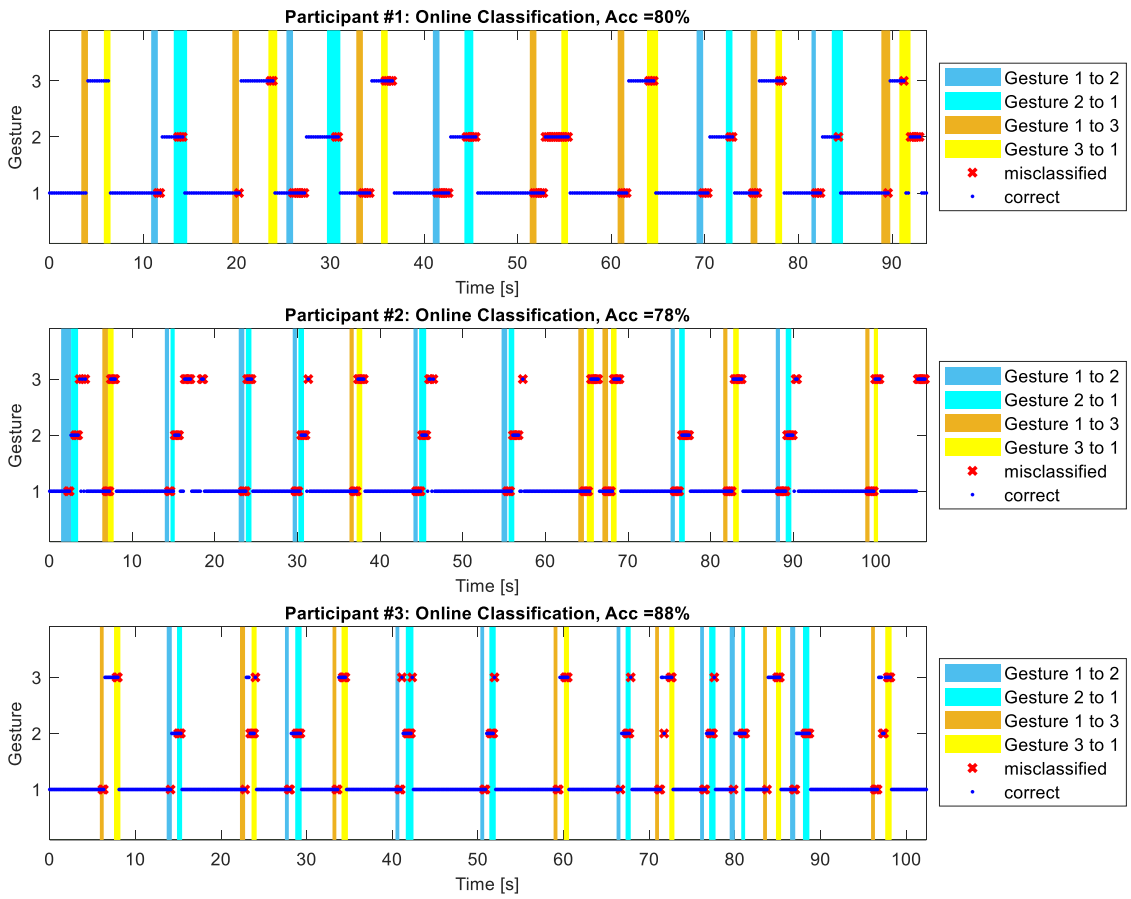

Figure 6-6: Online testing results for all three participants. Participants controlled a line-following robot with 3 gestures.

6.6. Summary and Future Work

Individuals with CP may suffer from severe physical disabilities, and therefore use different forms of assistive devices to increase interactions with their environment, community, and ADL. As presented in previous Chapters, an FMG band can be used as an assistive device to interface between a CP user and peripheral devices. However, further research is necessary to evaluate the robustness of the FMG band with additional CP participants since the symptoms may vary between individuals. The work presented here was initial research done with healthy participants to develop an experimental protocol for a future larger study with CP participants. The protocol utilizes the k-means clustering method of gesture selection that was described in Chapter 4.

After using gesture selection to find the top 3 gestures for 3 healthy participants, an LDA machine learning model was trained. A line-following robot called Vortex was programmed to follow a track and pause along the way until a particular gesture command was performed. The LDA model was able to predict gestures performed as the Vortex completed the set path with an average accuracy of 81.9±5.28%. It was observed that many samples were misclassified while the participant was transitioning from one gesture to another since the training is done with static gestures. Future iterations of this work should incorporate dynamic gestures during training as well as data collected during unconstrained time to ensure the gestures are not performed or similar to other actions done while completing ADL. Furthermore, participants should wear the FMG band on their lower limbs to gather a wide range of FMG data. The system design and built Android App will provide the groundwork for future studies with CP participants.

Chapter 7. Conclusions

7.1. Chapter Overview

This Chapter provides a summary of the findings from the research conducted for this Thesis. The following sections recall the objectives and relate the findings from the previous Chapters. Future research is suggested to continue towards the development of an FMG-based assistive device for individuals with CP and to test the k-means gesture selection method.

7.2. Summary of Objectives and Findings

CP is a term used for a series of symptoms ranging in severity, such as spasticity, tremors, and involuntary movement. It is often caused by injury to the brain during gestation or as an infant [4]. Individuals with CP suffer from physical, cognitive, and speech impairments. Motor control impairments can be summarized as: 1) a limited range of motion, 2) coordination problems, and 3) involuntary movements while executing a planned motion [13]. These impairments may affect ones' ability to complete ADL and communicate, leading to a lower quality of life. Many individuals who suffer from CP, rely on assistive devices to communicate and increase their independence and functional capabilities. A successful device must be easy to use, comfortable to wear, and have proper functionality. Additionally, many studies have discussed how false negatives may lead to frustration and abandonment of the device. Along with proper training, assistive devices should be introduced early in order to increase rates of retention. Thus, many inventions are simple enough for a child to use. Even classification systems tend focus on children as opposed to adults with CP.

There are a variety of ATs that individuals with CP may use based on their physical disorders and personal preferences. Simple single-state switches are one of the common forms at assistive devices. However, newer emerging technology such as BCIs are gaining momentum. BCIs, eye-gaze trackers, and multiple camera set-ups may be very beneficial for those with severe disabilities. Gesture recognition has been researched since the beginning of the 1980s and, with the increase lower-cost sensors, wearable devices have been gaining popularity. Wearable assistive devices translate a

user's movement into a command. Common wearable AT include EMG, MMG, flex sensors, IMUs, and FMG. FMG has been used with amputees, stroke, and healthy populations to capture gestures for rehabilitation and activity monitoring, however no research has been reported on FMG technology with CP populations.

A recent study [41] has shown the potential of FMG to be used as a wearable device that can interface with appliances, computers and communication devices with the aging population. This study formed the basis of designing a study to classify FMG signals with individuals with CP. A pilot study was conducted with an 18-year-old participant with hemiplegic CP. The participant wore an FMG band at the wrist and performed 5 gross-motor gestures. This study met **Objective 1** in this Thesis. **Objective 1** *was to determine if an FMG band can be used to classify upper limb force myography data in participants with CP*. Chapter 3 illustrated the feasibility of using a wearable FMG band with a CP participant. Three common machine learning algorithms were used to classify 5 gestures: 1) fist, 2) open fingers, 3) lateral rotation, 4) extension, and 5) flexion. The average cross-trial accuracy for all three classifiers were above 90%. Comparatively, in another pilot study [23] that used inertial sensors to classify four gestures using a perceptron algorithm the range of accuracy was only 60-70%.

One of the benefits of wearable ATs is that they rely on the motor capabilities of an individual. It is not necessary for the individual to be able to make a known gesture, such as a fist. Any repeatable, voluntary muscle contractions may be used as an access control with a FMG band. However, in a clinical setting, the therapist or researcher should be able to determine the set of muscle movements and/or gestures that are separable so they produce a high classification accuracy. Additionally, it would be beneficial to know the maximum number of gestures a user can perform with reliability and high classification accuracy.

This lead to **Objective 2,** which focused on *conducting a preliminary investigation to determine if k-means clustering can be implemented to lower the computation time of gesture selection for FMG upper limb data.* In Chapter 4, a study was presented that investigated using k-means clustering as a method to perform gesture selection. The study was conducted with 10 healthy participants who performed a set of 10 gestures while wearing the FMG band. After data collection k-means clustering was implemented to find sub-sets of the 10 gestures for a range of k values. In

each cluster, the gesture that had the most data samples belonging to a single cluster were selected. The data was then classified using three machine learning algorithms LDA, SVM, and kNN to find the cross-trial accuracy for each model. The time it took to perform the gesture selection was also recorded. The average accuracies across *k* classes for the three algorithms was 95.9 ± 4%, 94.7 ± 4%, 96.2 ± 3%, for LDA, SVM and kNN, respectively. For comparison, all possible gesture sub-set combinations of the 10 gestures were found and used to classify models using LDA, SVM, and kNN. The average accuracies, across *k* classes, were 98.3 ± 2%, 97.7 ± 2%, and 98.1 ± 0.0% for LDA, SVM and kNN. After conducting a two-way ANOVA and a Tukey range test, all 6 methods were found to have no statistic difference between their average means. In addition, the computational time for the k-means method was observably faster. The results from this study fulfilled **Objective 2** and laid out the ground work for **Objective 3**.

Objective 3 was to *explore using k-means clustering gesture selection to lower computational time in upper limb FMG data from participants with CP.* In the pilot study, outlined in Chapter 3, the upper-limb data from a participant with hemiplegic CP was used to perform gesture selection using k-means clustering. The participant wore the FMG band on their affected left forearm. The results show the average accuracies for the k-means clustering followed by classification using a machine learning model were above 98%, while just using machine learning to find the best gestures, had accuracies above 97%. The computation time for the k-means method was observably faster than all three machine learning algorithms. This result is in line with the known complexities of the different algorithms.

An experimental study was completed in Chapter 6 to evaluate the k-means gesture selection method and the FMG band with 3 healthy participants. The study provide groundwork for a possible larger study with CP populations. A variety of applications of the FMG band as an assistive device were investigated. Ultimately, participants controlled a line-following robot with three gestures on a set track. The control gestures were selected using the k-means gesture selection method from larger set of 12 finger and hand movements. The participants performed the gestures at a pre-determined location on the track. A trained LDA model predicted the gestures using online classification. The average testing accuracy for all participants was 82%. However, the results highlighted the need for collecting dynamic gestures for training because most of the misclassifications occurred during transitions between gestures.

Further studies need to be done to evaluate the robustness of the FMG band as an assistive device. The work presented in this Thesis only had 1 participant with CP. However, the diagnosis of CP has a broad definition and more participants are necessary to fully evaluate the band's performance under different forms of CP. Additionally, future studies should collect more gestures and muscle contractions to find the ideal number of movements that can be classified. This can be implemented using the k-means clustering validation method of finding silhouette coefficients and generating an elbow plot.

Although most commercial products undergo user testing, this is particularly necessary for assistive devices. As previously discussed, assistive devices need to be highly accurate and provide good functionality so the users and caregivers continue to use the assistive device. False-negatives can lead to frustration and possibly abandoning the assistive device. Future studies with FMG-based assistive devices should include sessions that could be done at-home where the participant can use the band over several sessions while, completing a scanning method activity or playing a game, for example. Additionally, the FMG band should be tested in an unconstrained environment, where the participants could complete a set of tasks from ADL while wearing the band, as shown in the study by Delva et al. [41] where the seniors were required to complete five ADL; 1) buttoning a shirt, 2) wiping a table, 3) picking up a cup, 4) opening a jar and 5) sorting a set of pens. During the data collection, the researchers can track if any of the access control gestures were perform by the participant and count the number of false negative and/or user-errors.

Although this work looked at using the FMG band for assistive devices, there is a need for rehabilitation and activity monitoring devices for individuals with CP. The goal of most rehab programs is to make quantitative and qualitative improvements in ADL to increase a person's independence [98]. For example, the FMG band has been shown to accurately monitor grasping in stroke participants [39]. It can be used to monitor how many functional actions were completed by the user in a given time frame. This would be of use for monitoring movement of the affected limb for a hemiplegic CP to combat development disregard. Future studies that take place over a longer period of time can investigate the FMG band as a rehab tool and to measure possible improvements in range of motion, muscle strength and reaction time. During those sessions input from the users, caregivers, families and healthcare professionals can be incorporated to

further the development of the FMG band as an assistive device and rehabilitation tool. Researchers have found that the development of ATs is driven by technological advances. Hence, it is important to include the target population in the development of any AT [99].

Three studies were designed and conducted towards the development of an FMG assistive device and a tool to select gestures using k-means clustering. This Thesis was able to show the feasibility of using FMG signals to classify gestures with CP populations. Additionally, a method of gesture selection using k-means clustering was implemented with a high classification accuracy. Although future research is necessary, these studies form the foundation for an FMG based assistive device.

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