Mechanical Redesign and Implementation of Intuitive User Input Methods for a Hand Exoskeleton Informed by User Studies on Individuals with Chronic Upper Limb Impairments

by

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Abstract

Nearly 3 million people in the United States alone suffer from upper limb motor deficits due to neurological conditions. With a diverse range of conditions causing this impairment, a wide variety of assistive and rehabilitative robotics have been employed to improve the quality of life for these individuals. While there are some existing assistive hand exoskeletons designed for flexion assistance, some hand exoskeletons designed for rehabilitation, and some designed for passive extension assistance, there is a need for an assistive hand exoskeleton for performing active extension and flexion in order to help individuals with hypertonicity and spacticity to perform activities of daily living.

The HOPE Hand, previously designed in the AIM Lab, set out to accomplish this goal. This thesis work evaluates the HOPE Hand by conducting the Box and Blocks Test for manual dexterity with an impaired subject, and identifies mechanical improvements to be on the hand orthosis. The HOPE Hand 2.0 was created by optimizing and revising the previous version. The HOPE Hand 2.0 allows the user to control two degrees of freedom for the thumb, one passive (abduction/adductions), one active (flexion and extension) and four degrees of freedom (flexion/extension) for the remaining four fingers.

After optimizing the mechanics of the hand exoskeleton, the next step was to design an intuitive user input method for device operation. Electromyography (EMG) has been commonly used in prosthetics and orthotics to control similar devices. Because of the muscle control challenges present in individuals with hypertonicity and spacticity, EMG control may be difficult for them to use. In order to evaluate the viability of conventional EMG methods as a user input method, a study was conducted on impaired and able-bodied individuals. The results of the study showed that 44% of the impaired subjects would be able to reliably use a conventional onset analysis or feature classification method of EMG control as they were implemented within this body of work.

To conclude the work presented in this thesis, the Box and Blocks test was repeated with the same impaired individual. The subject used the HOPE Hand 2.0 to lift blocks from one box to another by utilizing three methods: button press, EMG control, and voice recognition. The redesigned mechanics of the device proved to be reliable and functional. While the subject was only successful with the button press and voice recognition methods, the subject showed an interest in EMG control. This preliminary testing showed that all three method have great potential, although further testing is required to realize the extent of that potential.

Acknowledgments

This thesis work was made possible by the help of many. I would like to thank Katie, Paulo, Eduardo and the rest of my lab mates for always being willing to help me sort through my latest conundrum. Thank you to the patients and staff of Pine Bush Physical Therapy, as well as my friends at WPI for volunteering to be my study subjects. I need to thank my family who has always been so supportive of me pursuing my passions. Thank you to Chris, who introduced me to this project and taught me so much about the process, the goal, and the benefit of research, I will be forever grateful.

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Dedication

To the patients of Pine Bush Physical Therapy for giving me a reason to do research - you're my motivation!

And to Mom and Dad who have shown me the beauty of dedicating your life to helping people.

Preface

A Clinical Perspective on Robotic Solutions for Chronic Limb Impairments

There are plenty of research groups working on hand exoskeletons and other rehabilitation and assistive devices, so why are there so few on the market? In (Gassert & Dietz, 2018), Gassert discusses the lack of clinical relevance seen with a lot of devices from research groups. This observation was also one I made personally, which is why I decided to start a conversation. During the process of creating the hand exoskeleton for extension, our team worked closely with a physical therapist and an individual who would be the ideal candidate for the device. By interacting with the patient, we were able to get a thorough understanding of her muscle behavior and how she could use a device like ours to enable her to do more activities of daily living (ADL). If an engineer does not have a thorough understanding of the condition, the patients' needs could be misinterpreted. Engineers tend to read papers written by other engineers, who may misuse medical terminology or accidentally describe a medical condition in a way that leaves others with the wrong interpretation (Gassert & Dietz, 2018). This causes devices to be made for a slightly misguided purpose. being familiar with medical terminology enables engineers to communicate with other engineers on the requirements for designing an exoskeleton.

The physical therapist and the patient became invaluable members of the team, giving critical feedback throughout the design process. I wanted to inspire other students to seek this collaboration style, to bring together engineers, clinicians, and patients to discuss the existing gaps within assistive device market. To accomplish this goal, I helped organize an event which WPI Practice Point sponsored called "Practice Point Forum Series: Robotics Solutions for Chronic Limb Impairments." Throughout the day, we heard from patients, clinicians, academic researchers, and company representatives.

One of the key takeaways from the event was vocalized by a member of the clinician panel, that every device available to a patient is a tool that they can use to live independently. Within one population of patients, the device need varies wildly. Even during a single patient's rehabilitation process, their device needs will change. Therefore, our goal, as engineers should be to create these tools to continue to provide a range of solutions, increasing the inclusivity of available devices.

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List of Acronyms

ADL Activities of Daily Living
CMC Carpometacarpal Joint
CP Cerebral Palsy
DH Denavit-Hartenberg
DIP Distal Interphalangeal Joint
DoF Degrees of Freedom
GUI Graphical User Interface
EMG Electromyography
IMU Inertial Measurement
IP Interphalangeal Joint
MAV Mean Absolute Value
MCP Metacarpophalangeal Joint
PIP Proximal Interphalangeal Joint
RMS Root Mean Square
SPI Spinal Cord Injury
SSC Slope Sign Change
TBI Traumatic Brain Injury
UMNS Upper Motor Neuron Syndrome
WL Waveform Length
ZC Zero Crossings

Anatomy

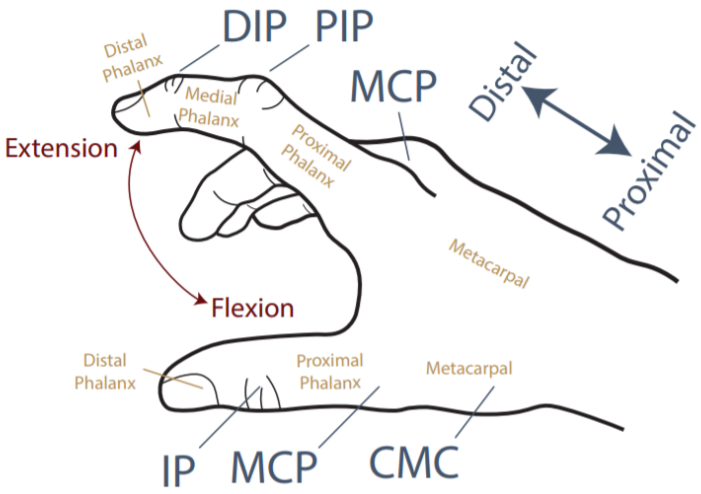

Figure 1: Labeled joints of the hand and anatomical terminology for motion and direction (Nycz, 2018)

1 Introduction

The biomedical robotics community has offered a number of solutions to address chronic limb impairments, including rehabilitative and assistive devices for the purposes of improving the lives of approximately three million people with upper limb motor deficits (Heo, Gu, Lee, Rhee, & Kim, 2012). Our research group and other academic groups have decided to focus robotic efforts on creating wearable, assistive exoskeletons aiming to restore/aid hand function for people who have a neurological condition known as upper motor neuron syndrome (UMNS). Some of the injuries/ illnesses that can result in UMNS are stroke, traumatic brain injury (TBI), cerebral palsy, and spinal cord injury (SCI).

The literature reveals a number of wearable hand exoskeletons designed to assist individuals in grasping tasks (Nycz et al., 2016; Arata et al., 2013; Gasser et al., 2017). Although these devices make a huge difference for a significant portion of the UMNS population, through our own research and informal interviews with clinicians and patients, we have identified a subset of the population that is currently being under-served. The tools that are available to these individuals, and within the research community, aren't currently able to provide the assistance they need (Nycz, 2018).

This subset of the UMNS population includes individuals that exhibit spacticity and hypertonicity, which results in a flexed arm and hand posture, making it nearly impossible for them to volitionally extend their fingers. Testing with an individual from this population was conducted to validate a hand exoskeleton from Vanderbilt University. The results showed that the user struggled the most with opening their hand to get it around a water bottle when they were attempting to complete the task without the hand exoskeleton (Gasser et al., 2017). This further verifies that finger extension is an action that requires assistance for a significant amount of individuals in the UMNS population.

Even though hand exoskeletons are becoming popular in research labs, there are very few commercially available (Shoemaker, 2018). One of the reasons for

this could be the lack of clinical testing being done in hand exoskeletons research (Gassert & Dietz, 2018). While it may be easy to identify limitations for the existing devices, it is important to realize there is no cure-all for assisting hand function for the UMNS community. It is a very diverse group of individuals in age, level of impairment, desire to be independent, and time since injury. What works for one person might be completely useless for another.

The work presented in this thesis aims to address the need for an extension assistance hand exoskeleton. We have brought patients and clinicians into the equation by conducting patient trials with the device. The Box and Blocks test, a tool commonly used by occupational therapists to evaluate manual dexterity, was used to evaluate the performance of the hand exoskeleton. This test provided valuable feedback on the mechanical design of the device and its limitations. Several improvements were identified and the exoskeleton was revised for better performance and comfort.

The next challenge in delivering a practical and successful assistive tool is implementing a reliable user input method for device operation. The user input method is a critical aspect of whether the device is accepted by the user or not. Electromyography (EMG) is a technique currently used in a lot of prosthetic devices to sense user muscle activity as motion intent to command the device to move. Depending on the reason for the limb absence, the individual will likely have a functional muscular system, which makes EMG an intuitive option. However, individuals who still have their hand, might not have very good muscle control if they experiencing a loss of function. This situation applies to the underserved population of individuals with hypertonia, and spacticity.

A study was conducted to see if EMG would be a viable option for device control for impaired subjects needing upper limb functional assistance. The results showed that 33% of the impaired subjects would be able to reliably use a conventional onset analysis EMG method to operate their assistive device and 22% would be able to reliably use a conventional feature classification method. These

results suggest that conventional EMG is not a viable option for device control for a significant number of individuals who are in need of an assistive upper limb device. Therefore further development should be made to EMG technology and algorithms for sensing intention of movement.

One of the main goals in wearable assistive devices is to be intuitive for the user to operate. Three user input methods were implemented to see how the patient would perform with the device and each control method. This includes manual control with a button press, EMG control with a simple threshold algorithm, and voice recognition control.

This research demonstrates the benefit of having clinicians and potential users involved with the design process. An improved version of the HOPE Hand was delivered after addressing the feedback from patient testing. This work demonstrates a need for further exploration of device input methods for the diverse user group. Final device testing showed that the HOPE Hand 2.0 has enabled a potential user to interact with her environment with her affected in hand in ways that she was previously unable.

A patient's care and treatment is a combination of physical therapy, occupational therapy, their prosthetist/orthotist, and their assistive devices. Creating an exoskeleton to perform a specific function such as active extension increases the inclusivity of available devices, adding another optional tool for patient treatment and recovery.

2 Background and Literature Review

In this chapter, the need for assistive hand exoskeletons and the conditions that they are intended for, will be discussed. Hand exoskeletons that are commonly cited within this field, will be reviewed to establish the context of my thesis work and how it fits into the existing environment of wearable robotic solutions. The conclusion of this chapter provides a short summary of the rest of the thesis work and my contributions.

2.1 Need for Assistive Hand Devices

Upper limb motor deficits can be caused by a neurological condition known as upper motor neuron syndrome (UMNS) or peripheral neuropathies, meaning dysfunction or damage to the peripheral nerves (Foad et al., 2008). Upper motor neuron syndrome, also known as upper motor neuron disorders, are conditions such as stroke (Bonita & Beaglehole, 1988; Benjamin et al., 2017), traumatic brain injury (Thurman et al., 1999; Walker & Pickett, 2007), cerebral palsy (Arneson et al., 2009; Arner, Eliasson, Nicklasson, Sommerstein, & Hägglund, 2008), multiple sclerosis (Goldenberg, 2012), and spinal cord injury, in which the nervous system is damaged within the brain and/or peripheral nerves. Figure 2 shows that there are approximately 3 million people in the United States that have upper limb motor deficits (Nycz, 2018).

This decreased voluntary motor function can make it hard for individuals to complete ADLs with their impaired limb and hand, making them ideal candidates for assistive devices such as exoskeletons. Because of the complexity of the nervous system and the unique nature of UMNS, this impaired hand function can be characterized very differently from person to person.

These motor deficits can be classified as hemiparesis (one side of the body), paresis, or paralysis which means an individual has little (paresis) to no (paralysis) volitional movement of muscles due to either "negative" symptoms or "positive" symptoms (Ivanhoe & Reistetter, 2004). Negative symptoms are characterized by

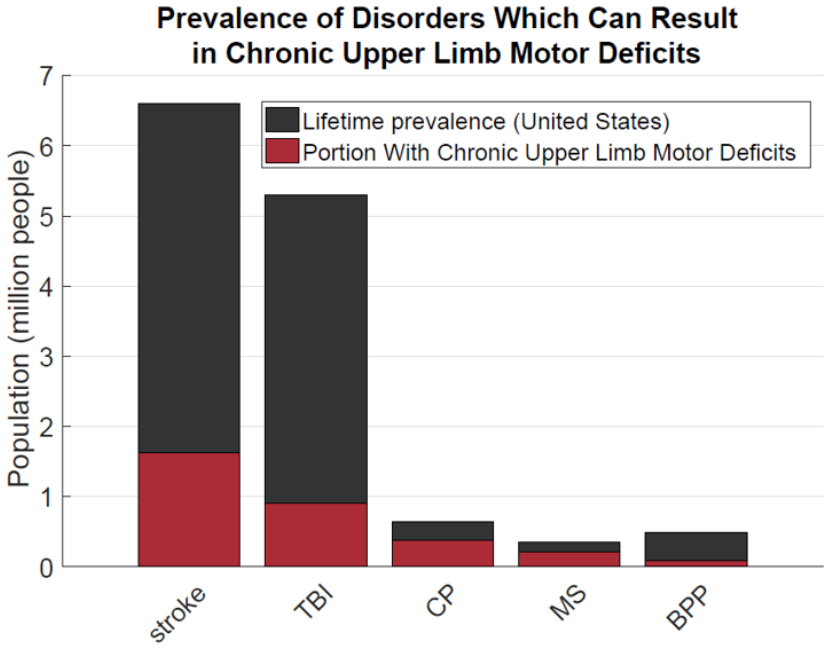

Figure 2: This chart shows a compilation of data from (Foad et al., 2008; Benjamin et al., 2017; Bonita & Beaglehole, 1988; Arneson et al., 2009; Thurman et al., 1999) of the amount of people who suffer from the conditions which can affect motor deficits in the United States (Nycz, 2018)

reduced muscle response and are generally known as weakness. Loss of dexterity is another phase associated with negative symptoms. Positive symptoms are characterized by overactive muscle tone and reflexes in which the muscle tension is uncontrolled. Spacticity and hypertonia are positive symptoms (Katz & Rymer, 1989; Sahrmann & Norton, 1977). The accepted definition of spacticity is a velocity dependant increase in muscle tone (Sahrmann & Norton, 1977). In the case of hemiparesis, the side of the body which has been impaired due to the injury or condition can be referred to as the "affected side" and will be referred to as such throughout this paper. Conversely, the side of the body which is unaffected by the injury, will be referred to as the "sound" side.

A common misconception is that an individual with UMNS presents with only positive or only negative symptoms. Many individuals have a combination of positive and negative symptoms that make their condition complex to understand and treat. For example, an individual with a flexor synergy pattern defined in (Chae, Yang, Park, & Labatia, 2002) is expressing clearly positive symptoms, but

they also have weakness in the muscles which prevent the arm from resisting the synergy pattern. Trying to understand how these muscle conditions interact by observing their physical body position as well as their muscle signaling can help researchers understand how they would interact with an assistive device.

2.2 Literature Review of Hand Exoskeletons

A review of notable hand exoskeletons has provided a landscape for which we can understand the gaps, and design a device to fill said gaps (Heo et al., 2012). A diverse group of devices is needed to provide assistance for a diverse group of impaired individuals. By evaluating the literature, we can see what design concepts have been successful and where there is some work needing to be done, thus allowing us to contribute a unique solution to the continuously developing landscape. The following hand exoskeleton devices have been chosen because of their relevance to this thesis work. While this is by no means an exhaustive list, these devices represent the main ideas and techniques people have used to assist motion of the hand.

2.2.1 ETH Zurich Glove

A novel hand exoskeleton for assistance was designed by J. Arata at Nagoya Institute of Technology in Japan. The mechanism for finger flexion is a three layer flat sliding spring which curves over the finger joint centers as the top flat spring slides over the fixed bottom flat spring. The entire hand exoskeleton is mounted on the dorsal surface of the hand which allows the palm and fingertips to be free grasping surfaces and makes it easier for the user to don and doff the device (Arata et al., 2013). Push pull Bowden cables are used to flex and extend the flat springs (see Figure 3), which allows the actuation unit to be remotely located on the user's back, reducing the weight of the device on the hand itself (Nycz et al., 2016; Arata et al., 2013). This device in intended for individuals with mainly negative symptoms, by assisting the finger flexion motion. A limitation of this

device is that it does not extend the finger, so individuals with positive symptoms may not be successful with this device. Another criticism of the flat spring design is that the length of the finger portion of the device does not change as the finger flexes. This means that the joints on the device change position relative to the actual finger joint. Nevertheless, the first version of the device was able to perform five different grasps. When the device was tested under a load of 3N at the finger tip, the device was able to withstand that load and perform flexion (Arata et al., 2013). Overall, the device is well designed, light weight, has a low profile on the hand, and is remotely actuated.

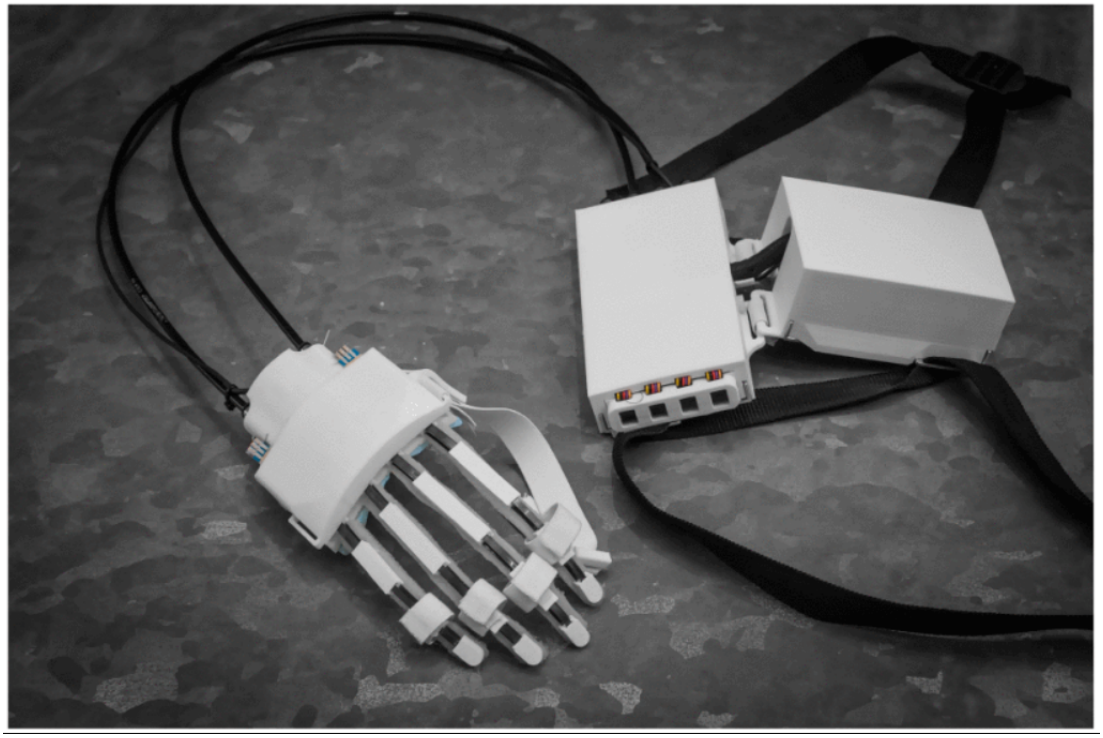

Figure 3: ETH Zurich hand exoskeleton with 3 layer flat sliding spring design and remote actuation unit which uses Bowden cables to move the sliding springs to flex the fingers and return them to an extended position (Nycz et al., 2016)

ETH Zurich produced a new version of this hand exoskeleton, called the RE-lab tenoexo, shown in the videos on their youtube channel (Alvarado & Arata, 2018). This new exoskeleton uses an under-sleeve with magnets for placement and positioning of the orthosis for easy donning. According to the video, it only took 2 minutes and 10 seconds to don and be ready for use. The new version of the glove uses the myoband to sense muscle activity in order to change positions

of the hand. The thumb design of the tenoexo enables the user to accomplish a wide variety of grasps using a sliding mechanism that can be manually adjusted. The thumb is able to externally rotate to accomplish finger opposition. Flexion of the thumb is performed actively with the flat spring mechanism. This thumb design is practical yet allows the user to have two degree of freedom in their thumb. The positioning of the metacarpalphalangeal (MCP) joint (Fig. 1) of each finger is not fixed, which allows for some adaptability between users, as well as accommodating movement during hand motions. The limitations from the previous version remain limitations in the newer version as far as lack of extension assistance, no extension of the device over the joint, and a low amount of grasping force. With that being said, the ETH Zurich/Arata hand exoskeleton could be successful in assisting an individual with weakened hands perform their activities of daily living.

2.2.2 Soft Actuators with Hydraulics

Another device that was built mainly for flexion assistance is the soft robotic glove from the Wyss Institute at Harvard (Fig. 4). Instead of being a purely assistive device, the intention of this glove is to combine assistance with at-home rehabilitation (Polygerinos et al., 2015). The soft actuators were designed in a way that different fiber reinforcement configurations could generate different motions for the fingers, such as extending, bending, and twisting. The natural finger trajectory during grasping was replicated using the soft actuators. The glove consisted of these soft actuators along the dorsal side of each finger including the thumb. Finger cups and straps made out of cloth were used to keep the hand exoskeleton in place. Tubing was connected to the soft hydraulic actuators which lead to a compressor on a waist belt which houses the rest of the electromechanical components as well. This glove aimed to exert a distal tip force of approximately 7.3N from each finger in order to achieve a palmar grasp of a object used in ADLs (Polygerinos et al., 2015). This is more than double the force that the

Arata glove could withstand/exert. However, this soft actuator hand weighs more than the Arata glove and the profile is substantially thicker. Because this glove was intended for rehabilitation, it is more acceptable to be a little heavier and thicker, as the subject is not expected to wear it throughout the day. In summation, the soft robotics hydraulic glove contributes to the landscape by providing a rehabilitation/assistive hybrid exoskeleton for providing flexion and grasping assistance.

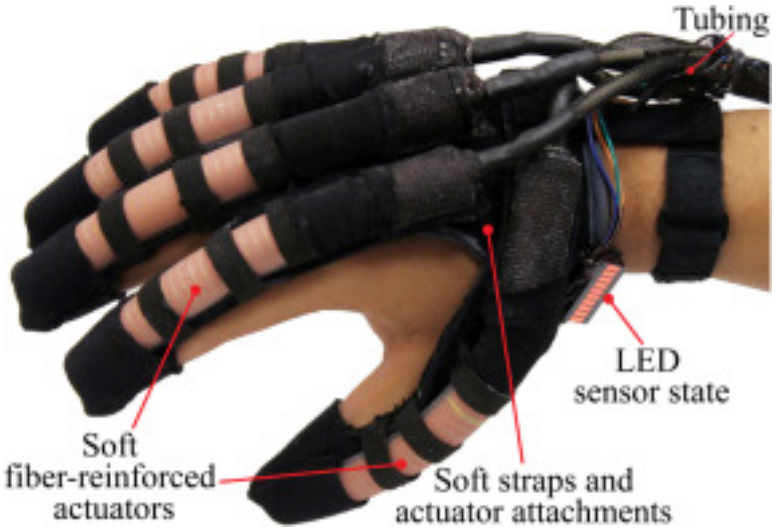

Figure 4: Hand Exoskeleton from the Wyss Institute at Harvard with soft hydraulic actuators for at home assistance and rehabilitation (Polygerinos et al., 2015)

2.2.3 SaeboFlex Glove

The J-glove was designed to perform constraint-induced therapy (Ochoa et al., 2009) as a means of at-home rehabilitation. With cables running down the dorsal side of each finger and joining at the base of the hand (Figure 5), the device can actively extend all of the fingers with one actuator. Used on individuals with mild to moderate hypertonicity, this glove brings the fingers through the extension motion, providing stretching and training for the muscles. Although it does assist the user to perform finger extension, the primary goal of this device is to perform therapy as opposed to daily functional assistance. One criticism is that the device is a glove which might be hard for users with a flexed hand posture

to don. This glove was tested on two healthy subjects and three stroke survivors, using EMG to sense muscle intention. Two out of the three impaired subjects were successful with EMG control, while the third impaired subject struggled to produce distinguishable muscle contractions for EMG control. Voice control and a button press were two other user input methods that were implemented. One suggestion they gave was to combine EMG control and voice control (Ochoa et al., 2009). While this device seems to be found only in a research setting, other products by Saebo are available on the market.

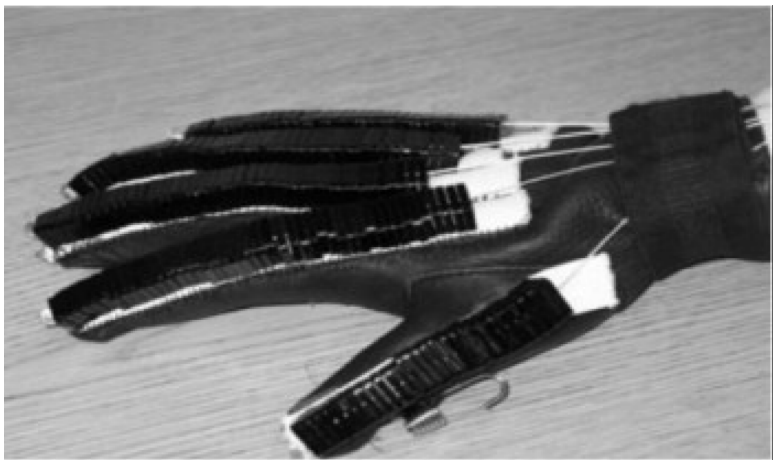

Figure 5: J-glove to perform finger extension for at-home rehabilitation from Saebo which was tested with voice recognition, electromyography, and manual control (Ochoa et al., 2009)

The SaeboGlove hand is a passive hand exoskeleton that uses rubber bands you can move to different resistances to maintain finger extension (Figure 6), with the goal being that the patient practices on performing volitional flexion. For the affordable price of $300 dollars, these devices have been met with success from users with mild to moderate hypertonicity and spacticity (*SaeboGlove | Finger Extension Rehabilitation Glove for Stroke Survivors*, n.d.). Again, for individuals with more severe spacticity and hypertonicity, it can be difficult to don a glove because the hand is in a fist position. These products provide an affordable solution for a subset of the UMNS population which needs passive finger extension, having mild to moderate positive symptoms.

Figure 6: SaeboGlove is an affordable device which performs passive finger extension using resistance bands (*SaeboGlove | Finger Extension Rehabilitation Glove for Stroke Survivors*, n.d.)

2.2.4 Vanderbilt Hand

An assistive hand exoskeleton for hand opening and closing was designed by M. Goldfarb's group at Vanderbilt University. Instead of moving each finger separately, all of the fingers are grouped together in the hand exoskeleton on the dorsal side of the hand, as seen in Figure 7. The intention of the device is to perform a cylindrical grasp, which is a practical use of the impaired hand within bi-manual tasks. The force which can be exerted on the finger tips is over 50N according to (Gasser et al., 2017). The thumb on this exoskeleton is a great feature as it can be adjusted to the length of the hand, length of the thumb, and rotation about the hand axis and the thumb axis.

The design evaluation conducted for this device was done on one impaired patient. The subject was tasked with grasping a water bottle, taking the cap off, and setting the bottle down. The metric for success was time; they timed how long each sub-task took with, and without, the hand exoskeleton. Their results showed that the most time-consuming sub-task without the hand exoskeleton, was grasping the bottle (Gasser et al., 2017). In total, it took the subject ap-

Figure 7: Hand Exoskeleton from Vanderbilt University moves all fingers together for successful power grasping (Gasser et al., 2017)

proximately 40 seconds to complete the task without the hand exoskeleton, and a little over 10 seconds to complete the task with the exoskeleton. This device sits within the landscape as being an assistive device for flexion and extension assistance in cylindrical grasping.

2.2.5 MyoPro by Myomo Inc.

As the only elbow, wrist, and hand exoskeleton device on the market, the MyoPro by Myomo Inc. (Cambridge, MA) has been very successful for some stroke survivors. The MyoPro uses motors to perform the gross motor functions of the upper limb, excluding the shoulder. The MyoPro is mainly a device for elbow flexion and extension but the hand component has also become popular (Fig. 8). The device uses EMG signals to trigger hand closing/opening motions, as well as elbow flexion and extension. A contributing factor for the success of the MyoPro is the simplicity and practicality of the design. Impaired individuals are looking for a reliable and straightforward solution which can be integrated into their daily life; Myomo has delivered this. While this device has certainly changed lives of some individuals, primarily those with weakness, there is a set of inclusionary criteria that disqualifies some individuals from being able to use the device. Some of

the inclusionary items are none to mild spacticity of the elbow, wrist, and fingers, full passive range of elbow and fingers, and a minimum shoulder flexion capability of 30 degrees (Peters et al., 2017). Being the only device on the market, there are currently a lot of impaired people without a solution for their hand impairments, even though there are several research groups working towards various devices for treatment and assistance.

Figure 8: MyoPro by Myomo, Inc. (Cambridge, MA) ; a commercially available powered elbow, wrist, hand wearable assistive device (Peters et al., 2017)

2.3 Device User Control Methods

When the mechanical design of an exoskeleton is finished, the next step in wearable assistive device development is deciding how the user will operate the device. The user input method should be intuitive, discreet, and reliable. Ideally, the user input method would also offer rehabilitative benefits. There are a few common strategies for user operation of upper extremity prosthetic and orthotic devices: button press, voice recognition controls, electromyography and other sensors like force sensors and accelerometers.

2.3.1 Button Press

The simplest method for reliable device user input is using a button press to change the state of the hand exoskeleton. Often times a button press has been implemented to validate a hand exoskeleton in the literature such as (Polygerinos et al., 2015; Gasser et al., 2017; Kang et al., 2016). This is because it is very easy to implement, and the intended movement is happening on command, because the user intention is clear. The button press can be used as a toggle, essentially. The button goes HIGH when pressed and the state switches. The state will not switch back until the button is pressed a second time, or a different button is pressed.

While it is easy to implement and reliable to use, a device operated by button control can be somewhat invasive, especially if the button location or manual requirement relies on another part of the body, especially the other hand. This further limits the capabilities of having two semi-functioning hands for bi-manual tasks.

2.3.2 Electromyography

Electromyography (EMG) sensors are used to record muscle activity in the form of a voltage generated by a muscle during contraction. Because of the high frequency nature of motor unit firings, the superposition of the individual firings results in a noisy-looking, random signal full of information (Contessa & De Luca, 2012). Researchers can process this muscle signal in numerous ways in an attempt to identify intentional muscle activations for EMG control. These methods of EMG signal processing for device control can be classified as either “pattern recognition" approaches and “non-pattern recognition” approaches (Hakonen et al., 2015). Both of theses approaches have been used to as control inputs for prosthetic and orthotic devices.

Two common non-pattern recognition approaches are onset detection and direct control. In the case of onset analysis, when an individual contracts their

muscles, the filtered signal will cross a threshold, set by the clinician at the time of fitting/tuning the device, indicating an intentional muscle contraction and telling the device to move. Onset analysis is used by the MyoPro (Shoemaker, 2018) to sense intentional contractions and actuate the elbow, hand and wrist. This approach is common because it is simple to implement and easily tuned for user satisfaction. Onset analysis would be considered a discrete method because the device is either in one state or another. Direct Control is continuous, meaning the resulting movement of the hand does not have a fixed amount of states. The idea is that the device would move at a speed proportionate to the intensity of the muscle contraction (Hakonen et al., 2015). Direct control is becoming more popular because it mimics natural movement.

The pattern recognition approaches generally refer to feature classification or "gesture recognition." Rather than recording muscle signals from one specific muscle, six to eight electrodes record muscle activity around the circumference of the forearm or upper arm. The specific combination of signals and features from all of the electrodes determine what gesture or state the person is attempting to change the device to.

EMG control, especially direct control, is a popular way for controlling prostheses; there are a number of prosthetic hands on the market that use EMG Control such as the LUKE arm by DEKA (*LUKE Arm Detail Page*, n.d.). Typically people missing their limbs have an intact nervous system, which is ideal for producing repeatable muscle contractions. Some prosthetic manufacturers are starting to use pattern recognition, but the majority of that work is being done in a research setting.

There is a misconception that a hand exoskeleton for an impaired individual is as easy to control with EMG as a prosthetic hand is for an amputee. Subjects who have impaired muscle control may not produce reliable, or predictable muscle signal, causing them to struggle with EMG user input methods. An example of this is in (Ochoa et al., 2009), when EMG control was tested with three im-

paired subjects and only two could reliably produce distinguishable EMG signals for the detection algorithm to recognize. This inability to repeatably provide intentional muscle contractions would also exclude an individual from qualifying for the MyoPro by Myomo (Peters et al., 2017) because it relies on user muscle signals.

2.3.3 Other Sensing Mechanisms for Control Input

In work by (Kang et al., 2016), researchers considered using a bending sensor (force sensing resistor) to utilize the tendonesis effect as their control input method. Tendonesis is the occurrence of finger flexion with wrist extension. This research group was designing for was spinal cord injury patients, who tend to exhibit tendonesis, but when the bending sensor method was tested in previous work, it was deemed too uncomfortable (In, Kang, Sin, & Cho, 2015).

Another sensor that is commonly used in robotics is an inertial measurement unit (IMU). The LUKE arm by DEKA Research and Development (Manchester, NH) is a futuristic, highly dexterous prosthetic hand/arm. They also developed wireless foot controls using IMUs (*LUKE Arm Detail Page*, n.d.). The IMUs are meant to be worn on the shoe, and the prosthetic hand moves depending on foot tilt, as if it were being controlled by a joystick. When the user starts to walk, the IMU is disabled, and re-engaged when the user stops. This control input is very discreet and although it would take some training, this system provides useful option for device users.

Voice control is a promising alternative to physical sensors. Rather than relying on the physical movement of a muscle or limb, voice control is only reliant on a person's ability to verbalize the intended commands. The J-glove implemented voice control using a commercially available voice recognition system (Ochoa et al., 2009) and they found it to be successful. However, injuries or conditions leading to upper limb impairment may also include damage to other parts of the brain, which could cause aphasia, which is the inability to understand or express

speech. Aphasia is common in individuals with stroke and TBI (Connolly, Mate-Kole, & Joyce, 1999) which means that voice control is also not a one-size-fits-all solution. Depending on how robust the voice recognition system is, it may also be difficult to use in a crowded room. In general, voice control could be a good option for people with adequate verbal skills.

2.4 HOPE Hand 1.0

This thesis work was preceded by another thesis project, at the end of which the HOPE Hand 1.0 was designed and constructed. I assisted with data processing for a grasping study and helped design and conduct a consecutive study on extension forces required to extend the fingers of TBI patients. These studies produced quantifiable specifications for the HOPE Hand. I also contributed to the design iteration process as well as the fabrication of the hand itself.

The HOPE (Hand Orthosis with Powered Extension) Hand 1.0 is a cable actuated hand exoskeleton for extension that was previously designed in the AIM lab. This design can be seen in Figure 9. Rigid plastic segments were 3D-printed in PLA for each finger link as well as a hand plate that directs the cables from the fingers to the wrist and up to the actuation unit, which was designed after (Nycz et al., 2016). Four motors were used to move each of the four fingers. The thumb could be manually positioned by loosening and tightening a screw such as in (Gasser et al., 2017). The device primarily lays on the back of the hand and around the fingertips, with straps around the palm and wrist to hold it on. The fingertips of the device were made out of cloth pockets sewn to 3D printed plastic segments. This device was intended to be worn throughout the day to assist the user in completing activities of daily living.

2.5 Summary

Each of these notable exoskeletons and control input methods have contributed to the field by providing a unique concept, device intent, or implementation. As you

Figure 9: The HOPE (Hand Orthosis for Performing Extension) Hand 1.0 seen in a complete package with the actuation unit on the upper arm and the hand orthosis.

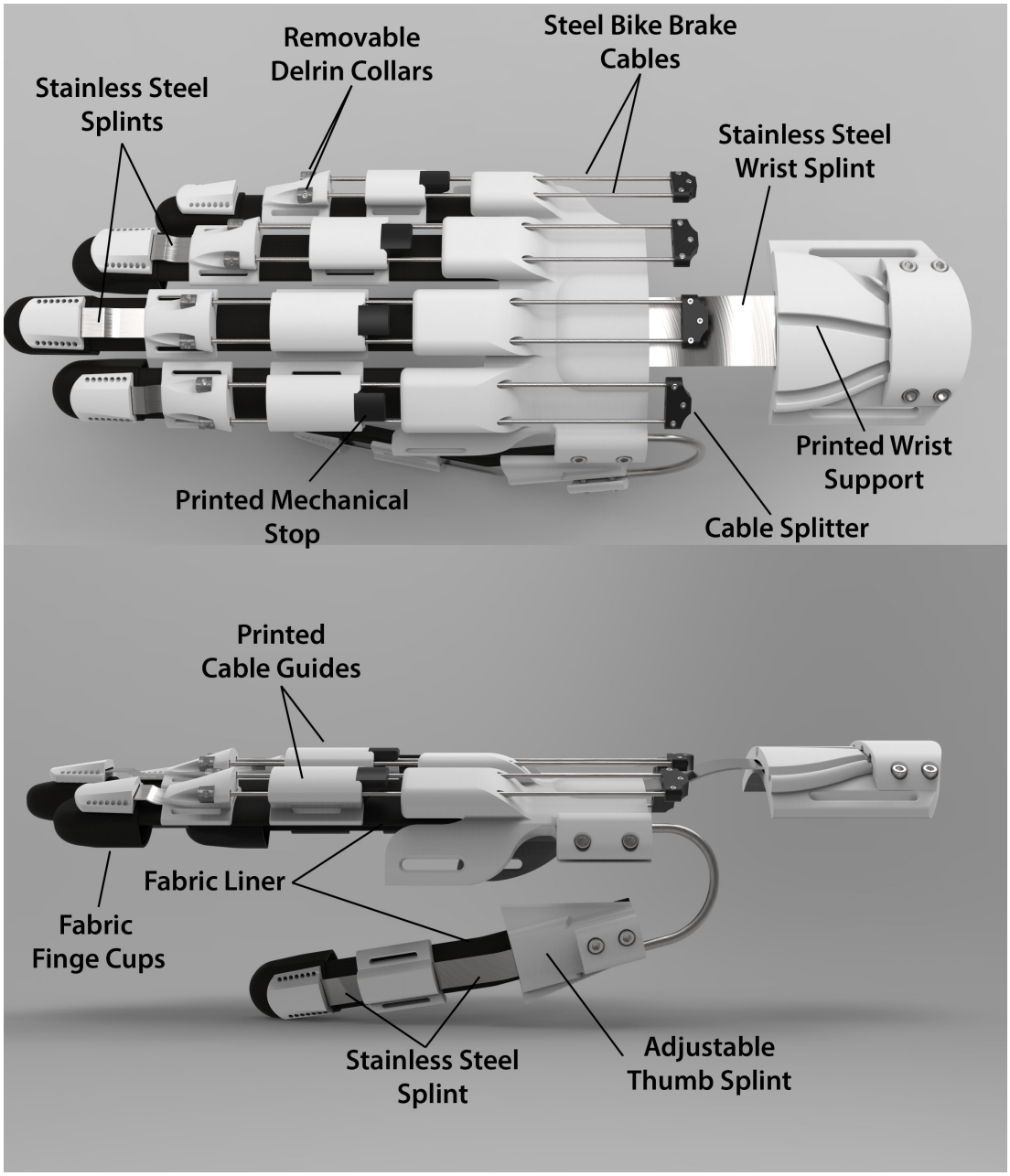

Figure 10: Rendering of the HOPE (Hand Orthosis for Performing Extension) Hand 1.0 annotated (Nycz, 2018)

can see, there is a remaining need for future development of hand exoskeletons with the focus being on providing an assistive device for finger extension for users with mild to severe positive symptoms. The device should be user tested, therapist approved, and intuitive for the user to activate.

2.6 Thesis Contributions

The AIM lab at WPI has been pursuing hand exoskeleton solutions for chronic hand impairment for several years. This thesis work builds upon previous student thesis and project work. The following contributions have been completed during my Masters thesis work, towards the goal of producing a wearable hand exoskeleton for assisting finger extension.

Contribution 1- Collecting valuable clinical testing data to evaluate the performance of the hand exoskeleton provides a real world perspective to designing devices. This also set a standard for future validation tests. By building a Box and Blocks set for the lab, I am enabling future researchers to use this test for manual dexterity.

Contribution 2- Improving upon the HOPE Hand 1.0, by adding two degrees of motion in the thumb and coupling the motion of the pinky and ring finger, increases the ability of the device to perform functional grasps while maintaining the actuator count at four.

Contribution 3- Exploring customization methods for fitting the hand exoskeleton using 3D scanning with the Kinect provides a future direction for projects. Inexpensive customization options are valuable to the patient, as they are more comfortable and affordable.

Contribution 4- The EMG data for impaired grasping is a resource that future researchers can use to create better techniques for EMG device control. A data collection protocol was established using the Delsys sensors.

Contribution 6- Writing EMG analysis MATLAB code for user control and using Delsys API to live-stream data for device operation is infrastructure that

will provide continuity for the project and provide future researchers a starting point for their work.

Contribution 7- A voice control option for the HOPE Hand was implemented using EasyVR which is an Arduino module. This method of device operation was preliminarily evaluated with an impaired subject during a second Box and Blocks Test.

2.7 Overview

In this chapter I've described the context for my thesis work by identifying a gap in the current state of hand exoskeletons.

In Chapter 3, I evaluate the HOPE Hand 1.0 by conducting a Box and Blocks test with a TBI patient. Improvements are identified.

In Chapter 4, mechanical revisions are made to the HOPE Hand 1.0 and the final design of the HOPE Hand 2.0 is presented.

In Chapter 5, a study is conducted to evaluate traditional EMG control as a viable option for the user input.

In Chapter 6, I implement three different control techniques, manual control with a button press, EMG control with a simple threshold technique, and voice control.

In Chapter 7, I conduct the Box and Blocks test again and the patient controlled the device with the three user input methods previously mentioned.

In Chapter 8, I discuss the work I have done for this thesis and how it impacts the community as well as the future work I would like to see for the further development of this field.

In Chapter 9, I discuss the other projects I have worked on throughout my graduate studies including a biofabrication project and a human driver motion study.

3 Evaluation of Hand Exoskeleton 1.0

Clinical testing is extremely beneficial for evaluating the device because you are closing the gap between the research project and the potential user. Clinical testing ensures that the device is clinically relevant and solves a real world problem (Gassert & Dietz, 2018).

3.1 Techniques for Evaluation of Patient Performance

There are several dozen impairment evaluation techniques that physical and occupational therapists can use to measure improvement of hand function and or to contextually quantify a person's physical condition in the presence of abnormal muscle tone. Some of these evaluation metrics include the Fugl-Meyer scale which is a quantitative evaluation of sensorimotor stroke recovery (Gladstone, Danells, & Black, 2002), and the modified Ashworth scale which is a tone assessment scale for spacticity (Gregson et al., 1999). After asking several therapists which metric is the most helpful in conveying the physical condition, they unanimously expressed that these evaluations are not very applicable to evaluating the hand in functional tasks. A basic test to show the performance of a functional task was needed in order to truly validate the current hand exoskeleton.

3.2 Box and Blocks Test

The Box and Blocks test was created decades ago to evaluate an manual dexterity (Mathiowetz et al., 1985). Occupational therapists often use this test to document a patient's initial condition and progress throughout their treatment. Engineers have started using this test to evaluate how well their device improves or replaces the functionality of the individual's hand such as (Kuiken, Dumanian, Lipschutz, Miller, & Stubblefield, 2004) which uses the Box and Blocks test to evaluate their prosthetic arm design. The procedure of this test, as well as the physical characteristics of the testing materials, are standardized, making the

results comparable to every administration of the test.

The testing materials consist of two wooden boxes with a partition extending beyond the height of the box in between the two boxes. One hundred and fifty colored, wooden, 1 inch cube blocks are put in the box on the subject's right. The subject is seated at a table with the testing materials in front of them, as seen in figure 11). The directions are read from a script as documented in (Mathiowetz et al., 1985), instructing the subject to move one block at a time from the box on the right, over the partition, and deposit the block into the box on the left. In order for the block to be counted, the fingertips of the subject must cross the partition. The subject is given 15 seconds to practice and 60 seconds to complete the test. The number of blocks that were successfully moved over the partition is the subject's score for that hand. The test is completed on both hands (if applicable) in order to compare the dexterity differences between hands. This comparison can be a useful tool if the subject is hemiparetic/hemiplegic because their sound side should provide a functioning baseline for comparison to their affected side.

3.3 Administering the Test

3.3.1 Getting a Baseline

The testing materials for the Box and Blocks test were created in accordance to the standards set in (Mathiowetz et al., 1985), and can be seen in Figure 13. The test was first administered to two able-bodied individuals on the research team for both hands in order to establish a baseline for average manual dexterity. The number of blocks transferred was between 53 and 63 for both able-bodied individuals.

A 22 year old subject with hemiparesis due to a traumatic brain injury was recruited for a study approved by the WPI IRB. The subject struggles to use her right arm due to a flexor synergy pattern, which is a arm position such that the elbow is contracted, the hand in a fist, and the wrist is externally rotated.

Figure 11: Box and Blocks Test being administered (Mathiowetz et al., 1985)

(Chae et al., 2002). The subject's hand experiences hypertonia, spasticity, and weakness which decreases her manual dexterity, making her an ideal candidate for a hand exoskeleton that performs extension.

The Box and Blocks test was administered to the hemiparetic subject. The subject was instructed to use her left hand (sound side) first, which proved to have average manual dexterity after comparing that measurement to the previous able bodied subjects (Fig. 13a). The subject then completed the test using her affected hand, resulting in no blocks being brought over the partition (Fig. 13b). These results can be seen in Table 1.

3.3.2 Performance with the HOPE Hand 1.0

The subject's performance of both her affected and able limb can be compared to her performance when she is using the hand exoskeleton for extension. However, before we are able to test with the hand exoskeleton, the device needed to be custom fit for the subject. The hand orthosis was resized and produced to fit the

subject's smaller hand, including only the thumb, index and middle fingers due to the grasping nature of the Box and Blocks test. The process of getting the correct fit started with requesting measurements of the length and width of her finger segments, as well as her palm. From there, test parts of the hand bracing were printed and evaluated for fit using my hand which is a similar size to the subject's hand.

After several iterations, the printed parts were a good fit for the subject's small hand, and the components were brought in pieces to the testing location to be custom assembled on the subject. The back plate and wrist piece of the orthosis were attached to the subject using fabric straps. Fabric strips lay across the back of the fingers and the printed finger segments were glued onto the fabric strips at the center of the finger segments. After the printed parts were secure, elastic bands around the fingers were tightened and the cables along the back of the fingers were adjusted to the proper length. The actuation unit was connected to the hand orthosis and attached to the upper arm, then the subject was able to fully don the device with the help of the researchers.

Some trial movements were initiated using a graphical user interface (GUI) made by the previous researcher on this project. Basic extension and flexion were performed using the hand exoskeleton. In preparation for the Blocks and Blocks test of the affected limb with the Hand Exoskeleton, the subject was instructed to say "open" when she wanted the researcher to activate "open" /extension using the GUI and "close" when she wanted the hand to be in the closed/ flexed position; this was essentially pseudo voice control.

The Box and Blocks test was initiated and the subject had difficulties positioning her hand in the box because her flexor synergy pattern inhibits elbow extension and shoulder flexion. Blocks were taken out of the box and placed on the table to give the subject a more comfortable workspace for picking up the blocks. The device was able to extend the fingers, but when the device was attempting to grasp the blocks, the subject was unsuccessful. Upon further at-

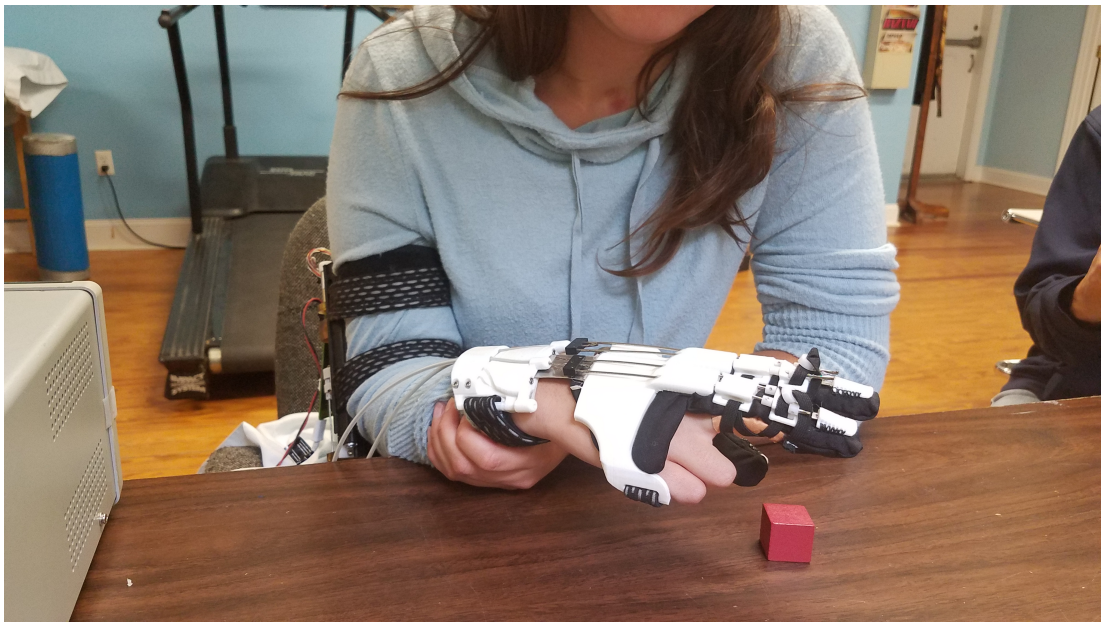

Figure 12: The subject wearing the HOPE Hand 1.0 which was customized to fit her hand

Figure 13: The subject completed the Box and Blocks test for manual dexterity with a) her sound side b) her impaired side and c) her impaired side with the hand exoskeleton

tempts to extend the fingers, the hand exoskeleton was unsuccessful; it could not provide repeatable full extension. The following items in the list are reasons why the device was unsuccessful in the overall Blocks and Blocks testing (Figure 13c). Table 1 shows the compiled results from the Box and Blocks test.

- Fingers were not able to fully extend
- Wrist was not stabilized
- Skin irritation and points of pressure
- Unable to perform functional grasps

Table 1: Box and Blocks with HOPE Hand 1.0

Test Condition	**Hand**	**Training(# of blocks)**	**Testing(# of blocks)**
Control 1	Sound	15	53
Control 2	Affected	0	0
HOPE Hand 1.0	Affected	Not Able	Not Able

3.4 Identification of Improvements to be Made

In this section I will expand upon the issues with the device, how the issues were temporarily solved during the testing session and the identified improvements that needed to be made.

After donning the device and initially attempting to extend the fingers and grasp a block, the block was pushed right under the hand without being grasped in between the thumb and the fingers. This was because the thumb was not positioned in opposition of the fingers in a functional way (Fig. 14). This suggests the need for a complete redesign of the thumb. A temporary solution was used to manually rotate the thumb towards the palm and bend the DIP ninety degrees. By positioning the thumb this way, the subject was able to grasp the block in between the flat surface of the distal thumb segment and the fingers. This grasp

is not typically used because a normal pinch grasp is more universally functional. The device should be able to successfully complete a pinch grasp.

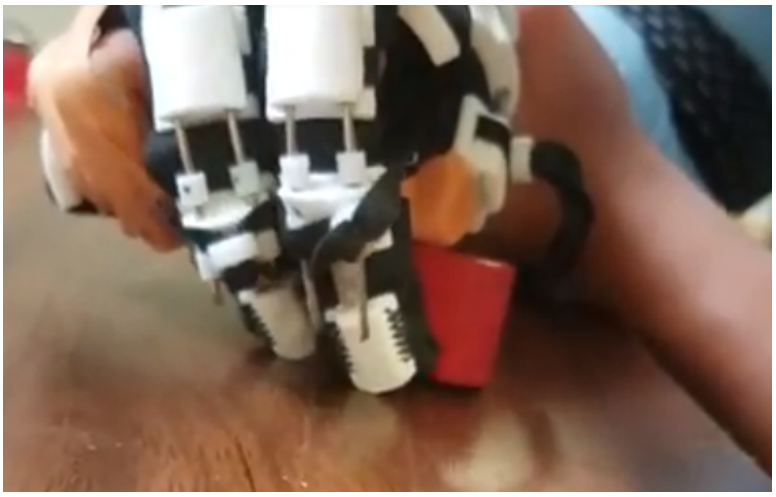

Figure 14: Inadequate grasp due to thumb position not opposing index and middle finger for proper pincer grasp

Because the pinch grasp was the desired functional movement for this test, the pinky and ring finger were not included in this production of the hand exoskeleton. This proved to be a slight issue because they remained curled into the palm, obstructing the palm grasping space. The block actually got stuck in the palm between the thumb and the ring finger, even though the finger was fully extended. To resolve this issue, the pinky and ring fingers were splinted and secured passively in the extended position. The pinky and ring finger move in tandem during most functional hand movements, therefore the exoskeleton should actuate both at the same time as well.

The subject's hand was generally relaxed at the beginning of the testing. As the subject started focusing on the challenging and repetitive task of picking up the blocks, her unintentional muscle activity increased, producing the flexor synergy pattern. The flexible aluminum wrist bracing on the device was unable to maintain a neutral wrist position, as you can see in Figure 15. This wrist flexion caused multiple problems with the device's mechanical performance. The first problem was that the cable coupler, which connects the finger cables to the Bowden cable, was repeatedly getting caught on the edge of the hand back plate.

This caused the cable to kink, putting stress on the actuation unit. To fix this problem temporarily, the kinked cable was replaced, the coupler's edge was filed down to create a rounded surface, and the wrist was braced more rigidly with a support added on the inside of the wrist. A permanent solution for wrist bracing was needed.

Figure 15: Wrist flexion cause by patient's hypertonia and very little wrist stabilization in the hand exoskeleton design

The flexed wrist also prevented repeatable finger extension. The cable lengths were adjusted intermittently throughout the testing by fully extending the fingers and tightening the mechanical stops to set the stroke length. By flexing the wrist, the distance between the forearm and the hand increases. This increase in length over the wrist limits the length of cable pull to extend the fingers, which results in an incomplete finger extension. Slippage of the set-screw-style mechanical stops also contributed to the device's inability to completely extend the fingers, along with the thicker fabric along the back of the fingers which bunched up in between the finger segment pieces.

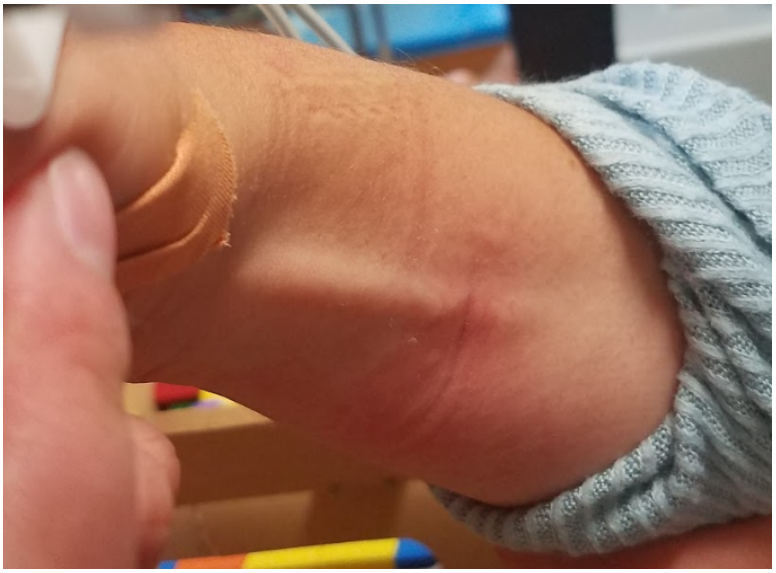

Figure 16: Moderate to severe skin irritation on the wrist from wrist bracing

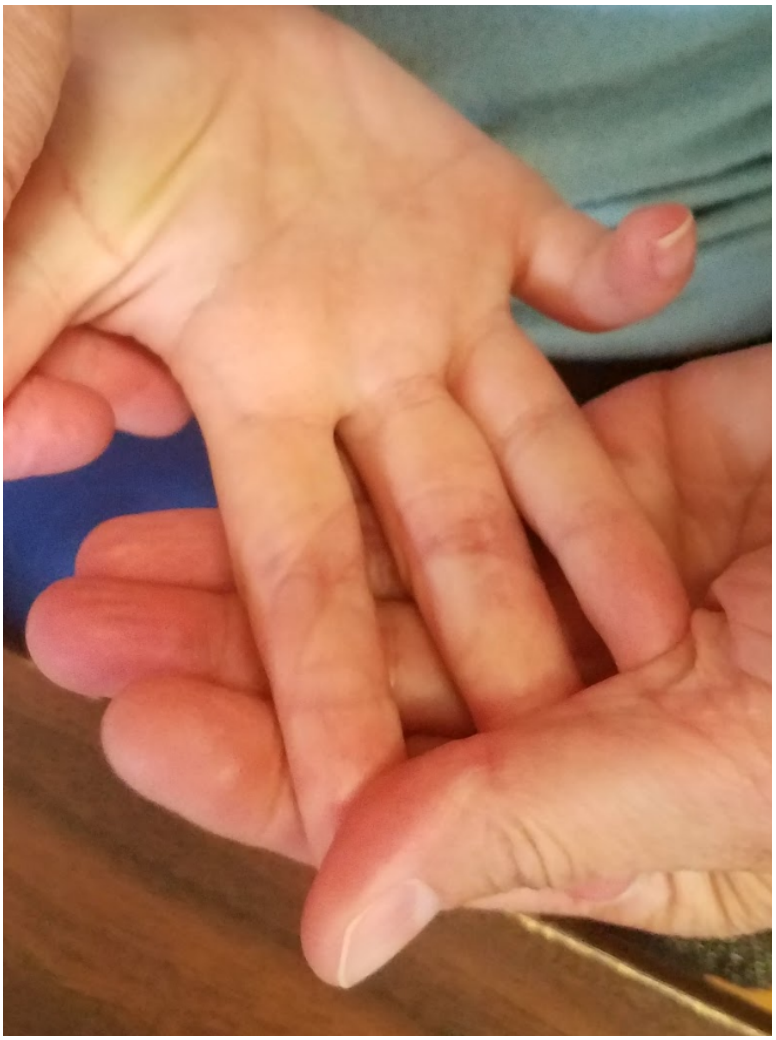

Figure 17: Palmar surface of the hand showing skin irritation on the fingers from elastic straps holding exoskeleton on the finger

The fabric finger cups of the device were too large which enabled the subject to bend their DIP, curling their fingers and, once again, preventing complete extension. The difficulty with simply decreasing the size of the finger cup is that it becomes increasingly difficult to don the device because of the unintentional curling of the fingers. During the testing, a temporary solution was employed. The DIP was splinted using short, thin, wooden, sticks and medical tape. This quick fix enabled the subject to successfully extend their fingers enough to get her fingers around the block.

When the testing session concluded, the device was doffed and irritated marks on the skin were observed (Fig.16, 17). When predicting the effects of daily irritation from a device, small marks can turn into pressure wounds and sores. While the observed marks were not a serious health risk after one session, they were documented and pictures were taken so they can be mitigated during the exoskeleton redesign. Ergonomics can make a huge difference with whether or not a user abandons a device.

After the temporary modifications were made to the device, the subject was able to pick up and place six blocks into the box from the table. This validated that permanent modifications could drastically increase the success of the device. The next chapter discusses the mechanical revisions that were made to the hand orthosis in order to improve the performance of the device.

3.5 Summary of Contributions

A Box and Blocks set was built according to standard dimensions and specifications in (Mathiowetz et al., 1985), to be used for future hand exoskeleton research in the AIM lab. Using the Box and Blocks test, a baseline evaluation of the HOPE Hand 1.0 was established, for which all subsequent iterations can be compared. Four major issues with the mechanical performance of the HOPE Hand were identified and documented as the following:

- Fingers were not able to fully extend

- Wrist was not stabilized
- Skin irritation and points of pressure
- Unable to perform functional grasps

These issues were mitigated on-site during the first Box and Blocks test using common household objects such as coffee stirrers and tape, which enabled the user to pick up six blocks from the table. These modifications provided proof on concept for the device, suggesting that a redesign of the HOPE Hand could succeed in improving impaired hand function.

4 Mechanical Redesign

The HOPE Hand is comprised of two parts, the actuation unit, which houses the motors and provides power to the hand exoskeleton, and the hand orthosis, which is the part of the device that the user wears on their hand. Because the actuation unit performed reliably during the user testing, the redesign did not include revisions of this part of the device. The mechanical redesign of the hand orthosis included modifications to the finger structures, the back of the hand, wrist and strapping, as well as additions to the original design including a thumb with two degrees of freedom and a pinky and ring finger coupling.

4.1 Finger Extension

Perhaps the most important problem needing a solution was the failure to repeatedly extend the fingers. The ideal fingertip for the device would splint the DIP joint (Fig. 1), be breathable and comfortable, and easy to don and doff. Several iterations of the fingertips were designed; the first being Figure 18 on the left. Rather than using cloth as the finger cup material, the finger cup was printed in a combination of vero clear and tango black to produce a flexible rubber. This design would be easy to don and doff, and it would reasonably splint the DIP. After trying this design on the subject from the Box and Blocks study, it was clear that the rubber finger cup was not breathable and not tight enough. After approximately 30 seconds wearing the finger cup, you could feel your skin getting sweaty and warm. If this design were only tested on the subject, this might have been a real issue because the subject has very little feeling in their fingers and would not be able to sense discomfort.

The second iteration of the fingertip design needed to be close fitting but breathable. Straps and fabric are breathable but they can cut off the circulation in the fingers and they can be hard for a user to don. Inspiration was taken from finger splints commonly used to immobilize joints in the case of injury or joint disorders. These finger splints utilize a three point technique where two points

of contact are on the underside of the distal finger segment and the medial finger segment, and the third point is on the top of the DIP joint. With the correct fit, the 3D printed part is comfortable, breathable, and restricts the DIP as necessary. This second iteration can be seen in Figure 18 in the middle. When this fingertip design was implemented, the volume of the sides of the fingers prevented the hand from closing, therefore, another solution was required.

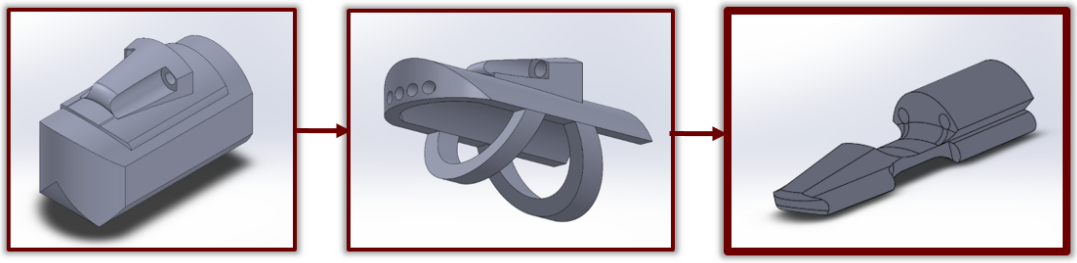

Figure 18: Fingertip design evolution (left to right) finger cup out of rubber, rigid finger splint, surface finger splint for tape attachment

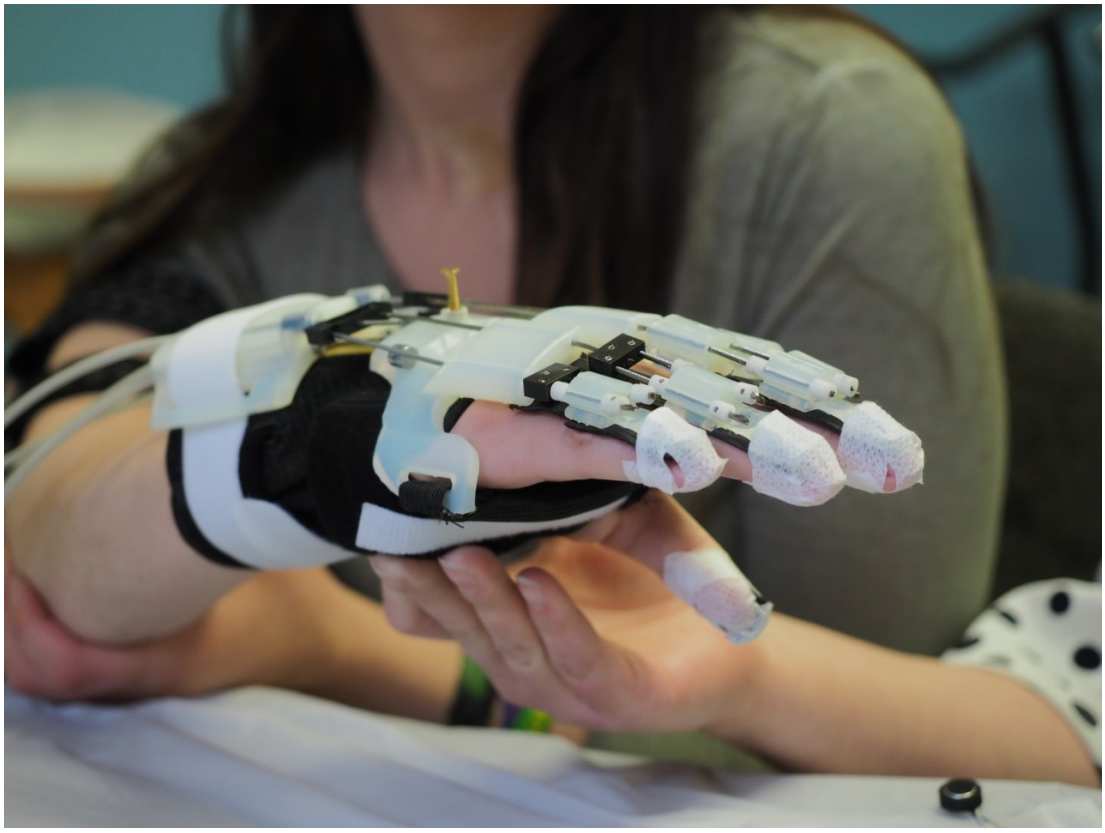

Figure 19: HOPE Hand 2.0 on subject with revised finger tip splint design, taped to the finger tip using T-shaped bandage

The third iteration was conceived after taking a step back in the brainstorming

process and thinking about what was successful about the original design. The cloth finger cups were comfortable, and were not thick on the sides of the fingers. During the Box and Blocks test, when the splinting needed to be added with medical tape as a temporary solution, the finger worked well. Therefore, the idea of using medical tape, was conceived. A finger splint was designed to lay on the back of the finger and attach using a strip of medical tape (Figure 18 on the right).

The medical tape used for attachment to the fingertip is called Cover-Roll Stretch by BSN medical which is designed to be flexible, waterproof and latex-free for wound care dressing (BSN, 2019). A template was created in the shape of an elongated "T" to produce pre-cut tape pieces, for easy application. In the future, a laser cutter could produce the "T" shaped and straight bandages for increased repeatability and ease of use. The "T" shape tape is donned by placing the cross of the "T" to the plastic finger tip, with the long center strip pointing upward, and the two sides extending to either side of the finger tip. The center strip was secured over the top of the finger, to the palmar surface of the fingertip, and then each side strip can be wrapped around the fingertip securing the plastic tip to the finger. Straight bandages made out of the same medical tape can be used to secure the remaining printed finger components.

This solution is breathable, it stabilizes the DIP, and it leaves the palmar surface of the fingers open (Figure 19). A touch screen device could still be used with the medical tape attachments, which is beneficial because these users may use touch screen devices as an assistive technology and as a part of their normal life. A caveat for the tape tip solution is that it is challenging for the user to don independently.

4.2 Functional Gripping Patterns

The two main gripping patterns are the key grasp and the three jaw chuck grasp which can be seen in Figure 20. While the current exoskeleton attempts a three

jaw chuck grasp, the revised design is intended to accomplish both grasps. In order for the exoskeleton to successfully demonstrate the two functional grasps, the actuation configuration needed to be optimized. With the old design using the four actuators, one per finger (pointer, middle, ring, pinky), the thumb was fixed in a static position which could be manually rotated with a set screw. Thumb flexion is essential for a key grasp and thumb abduction is essential for the three jaw chuck grasp. Therefore the thumb needed to be actively controlled and redesigned for two degrees of freedom movement. With four fingers left and three actuators, the clear choice was to couple the ring and pinky actuation due to the natural coupling of those fingers. There are very few functional hand positions that require either the ring finger or the pinky finger to be moved independently from one another. This reallocation of the actuators can be seen in Figure 21.

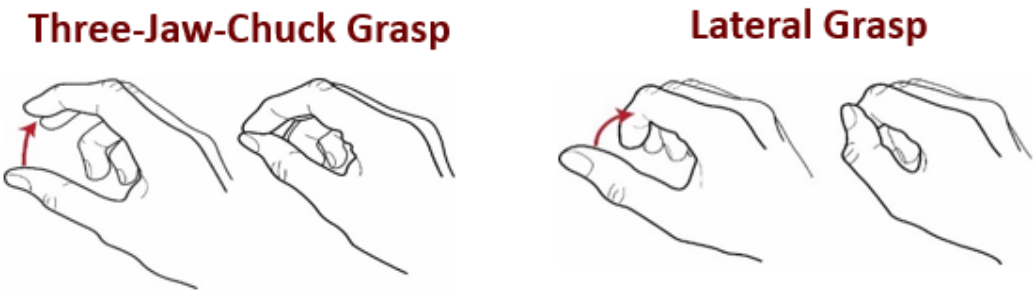

Figure 20: Two primary grasping patterns to be accomplished by hand orthoses to enable individuals to perform ADLs (Nycz, 2018)

The new thumb design was inspired by the tenoexo glove by ETH Zurich (Alvarado & Arata, 2018). In order to provide multiple grasping patterns with thumb motion, two degrees of freedom are built into the glove. Flexion and extension of the thumb is actively actuated by the cabling system on the device while adduction/abduction is passively controlled by manually positioning the thumb into a rotated posture (Fig. 22). A pivot pin is used at the base of the thumb near the trapezium, which is where the base of the thumb rotates, to ensure that abduction can be accomplished without displacing the hand exoskeleton from the thumb.

The ring and pinky have been re-designed to share a motor. The finger tip for

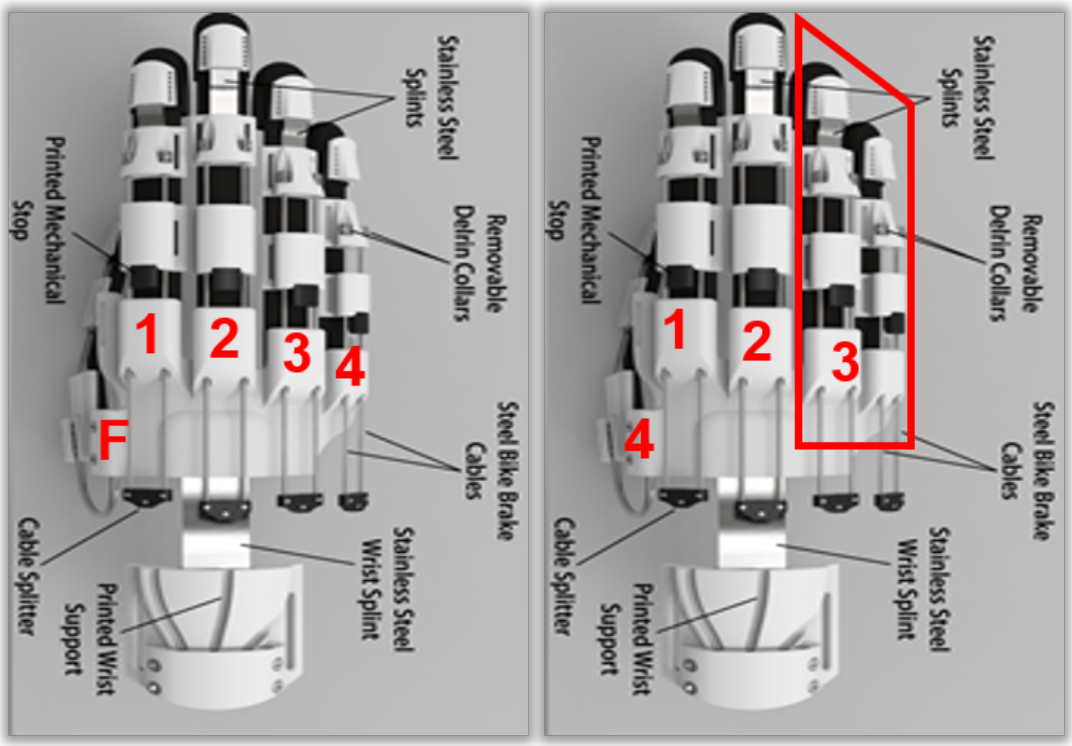

Figure 21: By reallocating the actuators from one on each finger (not thumb), to coupling the pinky and ring and allocating an actuator to the thumb, the HOPE Hand gained an active degree of freedom (HOPE HAND 1.0 render from (Nycz, 2018))

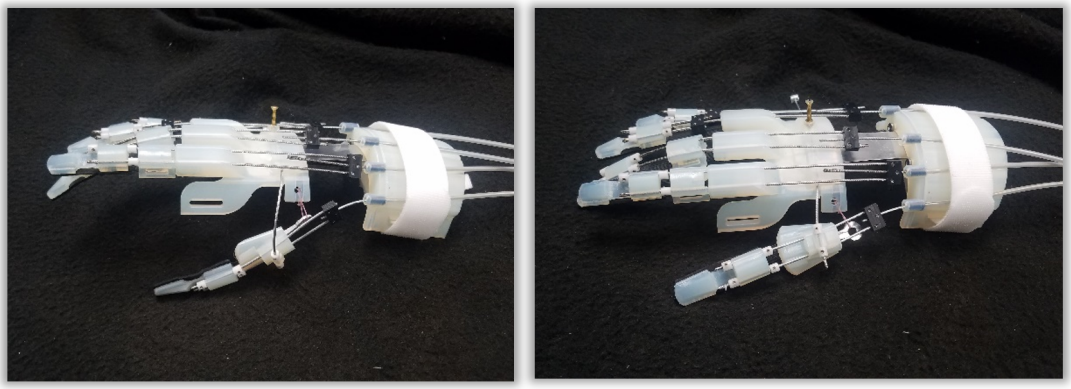

Figure 22: Thumb design provides two degrees of freedom in the thumb: abduction (on left) and adduction (on right), flexion and extension (with cables)

both the pinky finger and the ring finger were designed the same as the index and middle tip, however, instead of having a proximal guide for each finger, a coupler is used to connect the two cables on each finger, into one. At the proximal joint there is now a coupler on each finger with one cable connected to each, leading into the hand back plate. The two cables are then coupled together as the rest of the fingers are, leading to the actual Bowden cables (Fig. 23).

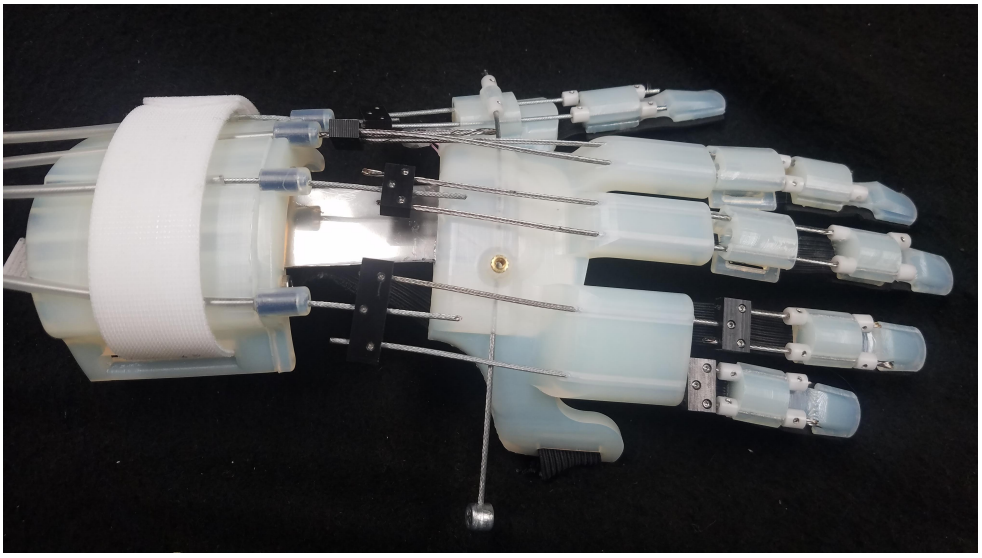

Figure 23: Pinky and ring finger are coupled by replacing the proximal cable guide with a coupler on each finger

4.3 Wrist Stabilization and Ergonomics

One of the major issues with the previous device design was the lack of wrist stabilization. The flexibility in the wrist prevented finger extension, caused problems with the Bowden cables, and made it difficult for the subject to position their hand around the block. The physical therapist confirmed that the wrist should remain in a neutral position to decrease tone in the hand, therefore finding comfortable wrist bracing that was easy to don became a priority. A BraceUP Wrist Support Brace with Splints for Carpal Tunnel Arthritis was found on Amazon and ordered. The brace was easy to slide on over a closed fist and tighten into place; it also successfully limited flexibility in the wrist. In (Alvarado & Arata, 2018) we see that the user puts on an undersleeve with magnets in it to position

the rigid exoskeleton on top of the hand. Drawing inspiration from that concept, the wrist stabilization component of the device was fully developed. Velcro was attached to the underside of the rigid hand back plate as well as the wrist plate (Fig. 25). Because the wrist brace already had a velcro outer surface, the orthosis was securely attached. The wrist bracing also acted as extra padding between the rigid exoskeleton and the skin, which made the device more comfortable.

Figure 24: BraceUP Wrist Support Brace with Splints for Carpal Tunnel Arthritis was used to maintain a neutral wrist position; velcro down the back surface allowed the rigid orthosis to be attached and removed easily

4.4 Metacarpal (MCP) Orientation and Support

During the Box and Blocks testing, the observing physical therapist commented on the position of the subject's MCP joint (Fig. 1) while the device moves the finger into extension. When the cables were pulling the fingers to extension, the MCP moved forward, causing slight hyperextension, which is uncomfortable and unsafe for the user. The therapist suggested adding a support to prevent the MCP from being pushed forward. During practical use of the device, it was

observed that the straight alignment of the cable guides from the MCP cause some collisions as the fingers flex into the palm. The orientation of the MCP cable guide should be stationary to mitigate abduction/adduction, but also in a natural orientation.

Maintaining the curved surface of the palm is extremely important for grasping, ergonomics, and enabling the hand to move in a safe way. There is a strap that crosses the palm over the MCP joints, but because of the positioning, the strap is tightened into a straight line, rather than following the curve of the palm. An elastic strap filled with foam was used to strap across the palm to provide this support (Fig. 25).

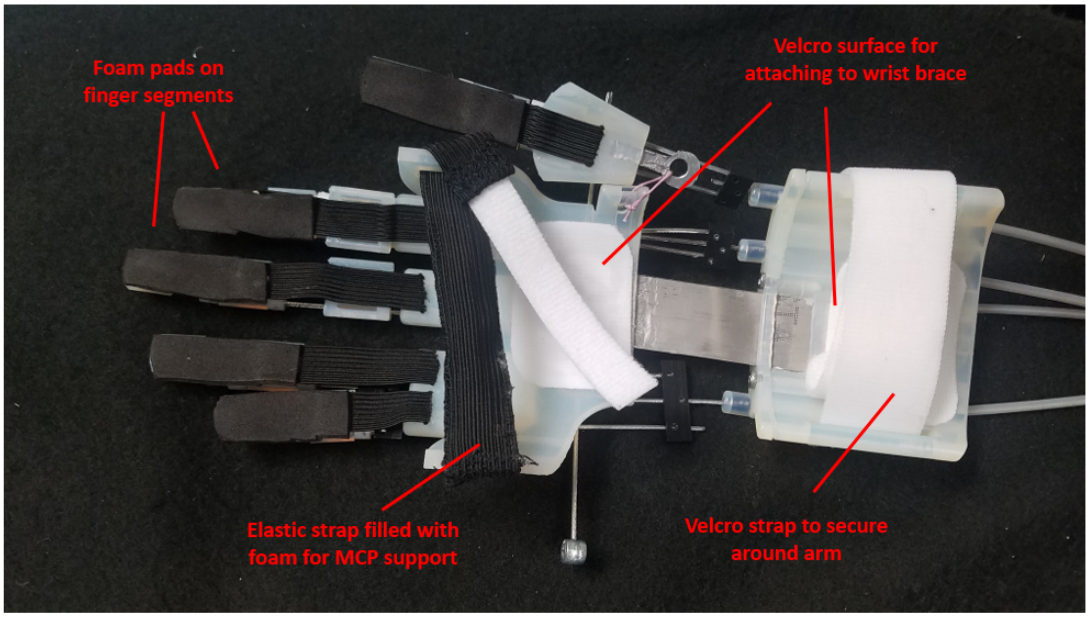

Figure 25: The underside of the HOPE Hand 2.0 features a strap to inhibit MCP hyper-extension, velcro to attached to the black wrist brace, and foam padding along the finger segments.

4.5 Final Design of Hand Exoskeleton 2.0

The HOPE Hand 2.0 is a redesigned version of the HOPE Hand 1.0. (Fig. 10). The redesigned hand exoskeleton maintains the same basic structure and function – consisting of an actuation unit with four Bowden cable drives and a hand orthosis, however the components of the hand orthosis have been modified.

The plastic component for the fingertip, subsequently referred to as the fingertip splint, spans from the distal end of the finger to the PIP along the dorsal surface of the finger (Fig. 1). The plastic component for guiding the cables across the proximal phalanx will subsequently be referred to as the proximal cable guide. The plastic piece that sits on the dorsal surface of the hand will be subsequently referred to as the hand back plate. The plastic piece on the wrist will be referred to as the wrist cable guide.

The solid components of the HOPE Hand 2.0, including the fingertip splint, proximal cable guides, hand back plate, and wrist cable guide, were made out of the "durable" material on the Formlabs Form 2 printer (Fig. 26). This material was perfect for the fingertip splints because it was compliant to a small degree, allowing the DIP to bend (5 degrees maximum), increasing comfort of the device.

An elastic strip connects the fingertip splints and proximal cable guide along the dorsal surface of the finger to the hand back plate. The placement of the components along the elastic strip is dependant on the user's finger segment lengths. After the elastic strips were attached to the proper length, black craft foam was glued on the underside of the fingertip piece to increase comfort of the device against the dorsal side of the finger tip (Fig. 25).

The cables are guided from the fingertip splint, through the proximal cable guides, and through the cable guides on the hand back plate to the Bowden cable housing on the wrist cable guide. The pinky and the ring finger were coupled prior to the cable guide in the hand back plate so the hand back plate cable guide is wider to accommodate centered cables from both the pink and the ring finger. Along the surface of the hand back plate there is a channel for another cable which is used to position the thumb passively in abduction. A hole for a thumb screw was place in the hand back plate in between the pinky and ring cable guide and the middle finger cable guide. This thumb screw is tightened to fix the thumb in position.

From the hand back plate, the cables were guided into the wrist cable guide

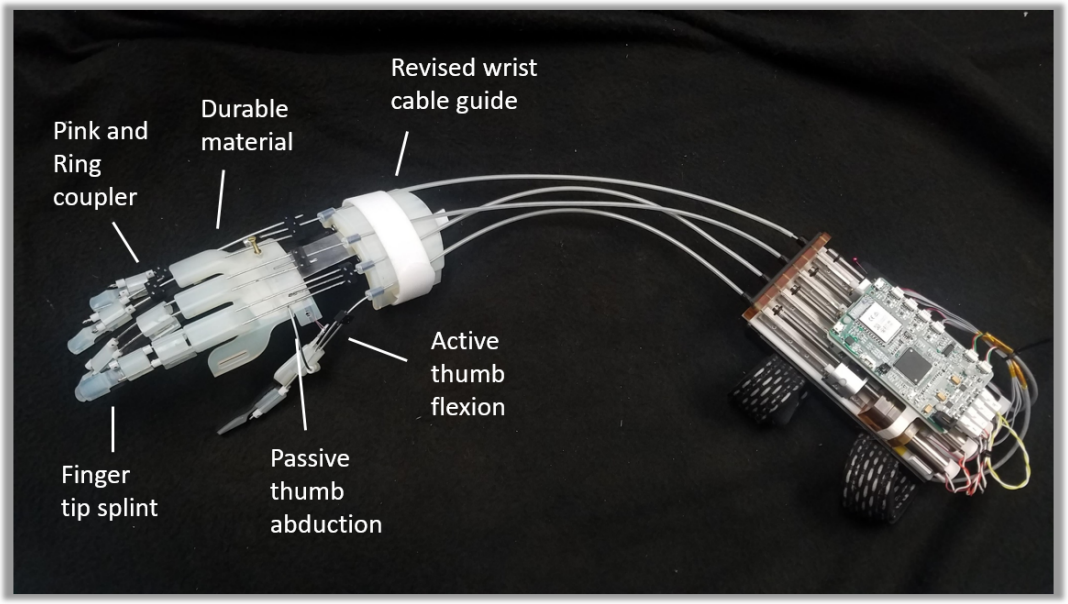

Figure 26: The HOPE Hand 2.0 final design

(Fig. 26), which was revised for cable efficiency by increasing the thickness of the part to prevent the couplers from catching on the edge of the hand back plate, and by adding another guide channel for the thumb for the active thumb flexion and extension. The revised wrist cable guide is larger than the original in thickness and in width but the cables are able to move in a straighter path, increasing the efficiency. Velcro along the underside of the hand orthosis is attached to the velcro on the back of the commercial wrist brace, tape is used to secure the fingertip splints and other finger segments to the user's hand, and the elastic palm strap is used to secure the hand orthosis to the wrist brace. These mechanisms keep the hand exoskeleton in place with a very small chance of it coming off the hand or migrating.

4.6 Exploratory Work with Device Customization using 3D Scanning

Within the field of orthotics and prosthetics, customization is key to a comfortable and effective device. Customization of devices can be difficult if there is a significant distance between the customer and the product manufacturer, re-

sulting in small adjustment and the device being sent back and forth, or long trips for either party. One way to make the customization process easier for the customer and the supplier is to automate, or semi-automate it. Through a biomedical robotics course at WPI, a project was done on customization of a hand exoskeleton through 3D Kinect scanning.

4.6.1 Protocol for Hand Scanning and Scan Processing

A protocol was created for scanning an individual's hand using a Kinect sensor and Skanect software to ensure high quality object files. The Kinect sensor was plugged into a wall outlet and a USB port on the computer. The device candidate had blue dots drawn on their hand in the locations seen in Figure 27a. These dots correspond to locations necessary for making key measurements on the hand. The subject sat in a chair at a table, in a well lit, spacious area. After the equipment and the subject were prepared, a researcher raised the Kinect to chest height, approximately one meter away from the subject, and the subject rested their hand at on the support structure. When the recording was started, the subject was instructed to remain as still as possible as the researcher slowly rotated around the hand, getting a satisfactory view of each of the blue dots. It was crucial to get views under the hand, above the hand, as well as from all sides to ensure high quality scans. The scan time was unlimited to ensure that all of the necessary data is collected, however most scans should only last two to three minutes. When the scan was complete, post-processing was be done within the Skanect software to colorize and smooth the 3D mesh. Finally the mesh was exported as an object file. The final image looked like Figure 27b.

The object file processing began with a MATLAB main script which reads the object file as a matrix of colored vertices. An average scan will have 250,000 to 750,000 vertices if it is properly cut down to size. Otherwise the scan can have more than two million vertices. Untrimmed scans that are very large can take several minutes to read into MATLAB. All of the code for the post-processing of the

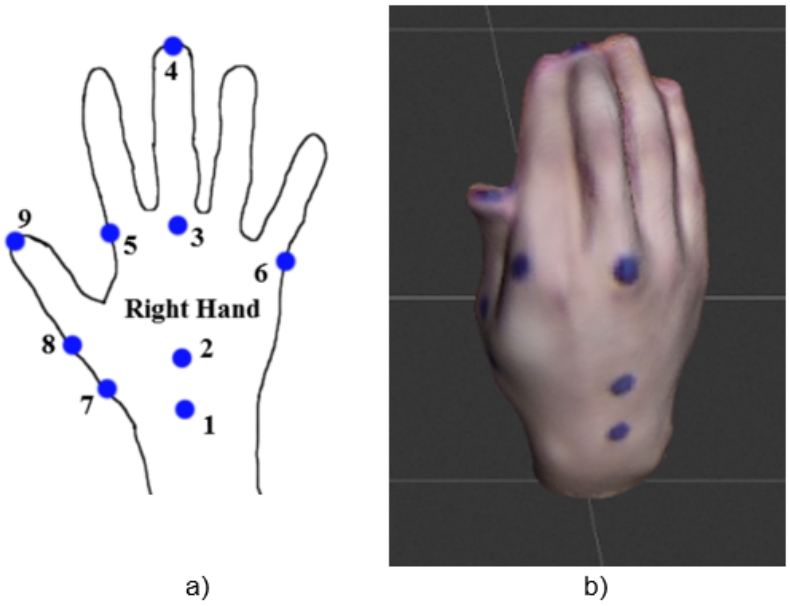

Figure 27: Locations used for making key hand measurements a) in a graphic for reference when drawing on the hand b) after the scan has been taken and the mesh has been colorized

scan can be found at this public Git repository: https://github.com/swhiteinventor/RBE_580_Biomedical_Project.

An HSV color filter was implemented and typically removed around 99% of the total number of vertices (Fig. 28a). Then the vertices matrix is converted to a point cloud for all remaining operations. Next, the point cloud is grouped into clusters of local points separated by some distance from other clusters (Fig. 28b). Filtering out clusters that are too small or too large typically leaves 11-17 remaining clusters. At this point, the centroids of the remaining clusters was known, but the order and relevance of each cluster was still unknown. The researcher then has the ability to label each cluster either as a number corresponding to a provided diagram or as "not a marker." This process iterates through all the remaining clusters, returning a matrix of the centroid locations of the ordered markers when completed.

To obtain the anthropometric data used throughout this project, we evaluated team members' hands, and accepted average values to derive data. The

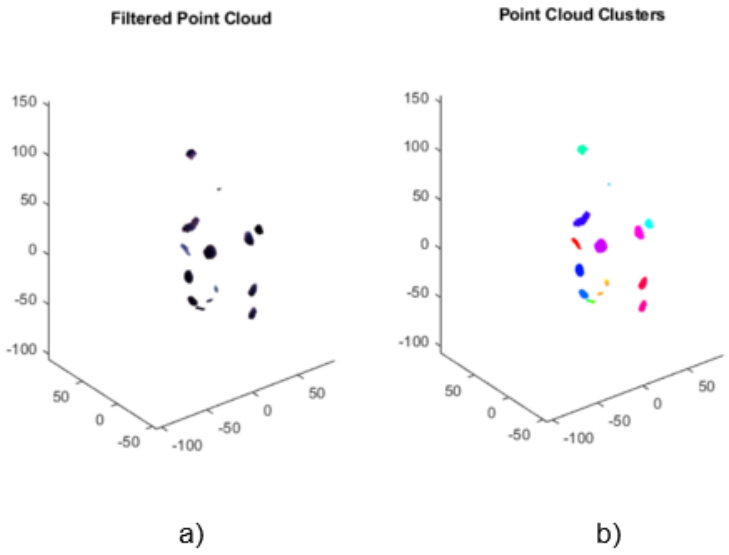

Figure 28: Identifying locations of markers with cluster a) filtered point cloud showing all verticies within desired color range b) individuals clusters in different colors

data collection was exempt from IRB approval because it was conducted in an educational setting. Utilizing a chosen 22 points on the hand, approximately 30 different lengths were generated and used for kinematic and SolidWorks models. Finger ratios were found using a reference finger length. This reference length was determined by measuring the middle finger from the tip to the dorsum point. From there, each finger measurement was compared to the reference length to determine a ratio. The thumb ratio was found separately using the total thumb length as the reference length. The remaining thumb measurements were determined using the same method as the other fingers, but compared to the thumb reference length. The metacarpal distances were compared to a reference palm length. These ratios were compiled, and overall average ratios were calculated (Appendix A 56). To determine more accurate data points, ratios were separated for male and female values. These ratios were then used along with four predetermined measurements to parameterize the CAD models for the rigid hand exoskeleton parts. These ratios were used in a MATLAB function to take nine marker locations from the hand scan and calculate approximately 30 parameters

for the kinematic hand model and for the CAD parts. The function output the kinematic parameters to be the input parameters for the kinematic hand function, and also generated a text file of global variables to input into the design table in SolidWorks for each part.

4.6.2 Kinematic Hand Model Results

The kinematic model was developed based on previous work for the Robomec Robot Hand (RRH) (Lee et al., 2012). However, they just considered three fingers and the thumb. We have included the pinky finger because, for our wearable prototype, it is necessary to consider the total width of the hand. Additionally, RRH provides 13 degrees of freedom (DoF) while our model provides 16 DoF. As in the RRH, we expressed the kinematic relationship by the Denavit-Hartenberg (DH) parameters. To accomplish this, we generated a MATLAB script. The inputs are the calculated measurements for each finger, the palm and thumb. These measurements correspond to the distal phalanx, middle phalanx and proximal phalanx of each finger. Five measurements are necessary to generate the thumb kinematics: the distal and proximal phalanx, metacarpal, trapezoid and scaphoid. Additionally, it is necessary for the four metacarpus of each finger and the distance between the center of the four finger knuckles. Furthermore, we settled the global origin in the extreme of the hand, aligned with the edge of the pinky finger. For the thumb, we analyzed the movement angle with respect to the global origin in the same plane. Then we settled the origin of each finger. We implemented the finger knuckle distance from the global origin to align the center line of each finger with their corresponding origin. The transformation matrix of each finger origin was multiplied by the transformation matrix of the fingers, aligning the joints of the hand and creating a kinematic model of the hand which can be seen in Figure 29.

We have tested the kinematic model with real hand measurements and angles. Moreover, we overlaid a hand image to visualize the accuracy of the hand model

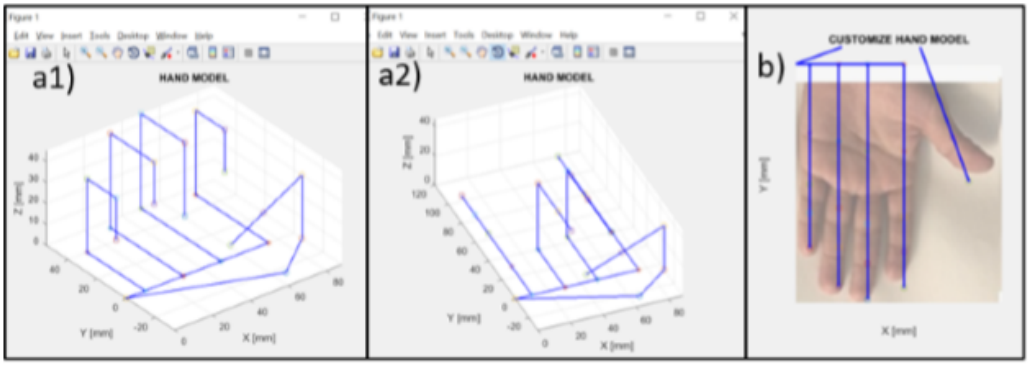

Figure 29: Kinematic model of the hand, expanded from model in RRH (Lee et al., 2012) using hand measurements a1) flat hand a2) hand with middle, ring, and thumb bent b) kinematic model overlaid with photo of hand

(Fig. 29b). However, we faced some problems when we tried to use the calculated measurements from the scan to generate the kinematic model due to the position of the hand while it was scanned.

4.6.3 Parameterization of 3D SolidWorks Model Results

Key dimensions that were extracted from the processed object file were sent to a text file that could be linked to each solid part used for CAD 3D modeling. At the beginning of the parameterization process, each of the existing SolidWorks files were opened and assessed to simplify the holding sketches and dimensions, as well as certain equations, to eliminate redundancies and ensure the models would be easily compatible with the new key measurements being input as global variables. The original CAD models were also assessed to record their original dimensions and identify which ones were most important in the part generation. These were compiled in a spreadsheet available in Appendix A55. Next, a different team member measured their own hand dimensions to create a series of secondary models to use for a test print, in order to confirm that the proper length adjustments allowed for a similarly well-fitting exoskeleton.

A spreadsheet was put together with the names of each CAD file (one for each part) and the dimensions that were relevant for customization, available in Appendix A. It includes the five key hand dimensions, their corresponding anthro-

pometric data, the team members own measurements, and a variety of ratios and formula-based cells that were used to calculate the proper lengths of the global variables for the standardized CAD parts. The global variables were gradually reduced to just two per part file, introducing key anthropometric dimensions including hand breadth, hand length, thumb length, third finger length, and dorsal length. Furthermore, the equations included in the table of each part typically had to be edited, ensuring that any variations to the size of the model would be accounted for properly and would permit a scaled model that maintained its design integrity. This was largely done through writing algebraic relations between relevant dimensions.

Once the models were all considered robust and effectively editable, with the two relevant global variables assigned to each (listed in Appendix A55), each model was linked to the text file (with the link to external file option from the equations table of the tools menu) that contained the customized hand dimensions based on the actual scans. This way, the model would practically draw its dimensions directly from the source. The next step in the process was to save each part as an mesh file and send it to a 3D printer for additive manufacturing. The qualitative fit of the process-based 3D printed exoskeleton is necessary to assess whether the physical measurements, anthropometric data ratios (Appendix A56), and scanned hand kinematic model were able to proceed in conjunction throughout the project pipeline and produce a well-fitting physical product in the additive manufacturing stage.

4.6.4 Discussion of 3D scanning for customization

The motivation behind this project was to reduce human error, reduce burden on the researcher/clinician, increase repeatably, and allow for remote access to physical geometry of the subject's hand. While the pipeline is intact, some of the motivations have not yet been fulfilled. There is still room for human error when the blue dots are being drawn on the hand. Even though the locations

are specified and shown in a photo, the placement could be off. For many of the marker placements you can palpate for bony landmarks and get an accurate placement, but for a few of them you really have to be able to visualize the kinematic model, which a clinician might never have seen. If the pipeline was fully automated then the burden on the researcher and physician would be greatly reduced. This would mean that within five minutes, the scan could be taken and the 3D part files could be generated without doing anything other than clicking through a short protocol. As far as allowing for remote access to the physical geometry, the scanning process is superior. Even if the researcher would like to get a measurement that is not currently marked with dots, they can add markers to the object file using a mesh editor.

For the kinematic model we faced some issues with the calculated measurements. These measurements considered the distance among the centroids of a curved hand. In this scenario the lengths are shorter. This problem could be fixed by making hand scans in a flat position. In the CAD model, parameterization segment of the project, there were a couple of difficulties that were encountered. Primarily, they were within the equations table. Adding more parametric equations always seemed to raise the risk of getting a "the syntax is not correct" error pop-up, usually due to an incorrect reference or simply not having the equations in the right order. This was compounded by the difficulty in reorganizing the equations, as the option to do so automatically was often disabled. In this case, it was very tedious to reformat the equations without crashing the part due to undefined or missing references

Another difficulty was in making the parts robust, as they were initially designed to fit just one hand size. For this project, it was important to allow for effective resizing, over a range of dimensions, and so the algebraic constraints that we built into the new models needed reflect that. This occasionally became problematic when the geometric integrity of the part was jeopardized upon re-sizing. To fix this, more relations should be established and the sketch should be defined

with variables instead of numbers. Future work could be done on this project as far as extracting measurements and curvatures from the hand scan. Another area for future development is making the 3D printed parts more robust to varying sizes. The integration of this pipeline still requires some manual intervention, which should be minimized in future developments.

By working to ease the production of the exoskeleton through a semi-automated pipeline, this technology can eventually be used to quickly fit patients with their hand exoskeletons, eliminating frequent visits for fitting adjustments. This requires adjusting the manufacturing process so that parts can be customized for specific patients using 3D scans of the patient's impaired hand. With this customizable process, patients will have care designed specifically for them, allowing them to regain control of their limbs again, and researchers will be able to evaluate these devices more efficiently for patient use with fewer adjustments needed.

Thank you to Samuel White, Alex Chiluisa, Kara Martin, and Reynaldo Duran for their contributions to this course project; it was truly a team effort.

4.7 Summary of Contributions

A new fingertip piece was designed to improve the repeatability of finger extension. This design rigidly splints the DIP and uses medical tape to secure device to user. The actuators and Bowden cables were reallocated to provide active thumb flexion and extension by enabling the use of one actuator for both the pinky and ring finger. In addition to the active flexion and extension of the thumb, the redesign included a passive thumb mechanism that positions the thumb in adduction or abduction. This mechanism uses a cable attached to the proximal thumb segment, guided through a channel on the back of the hand, to achieve rotation at the MCP. A commercial wrist brace called BraceUp was integrated into the device as an under-sleeve to improve wrist stability. This brace splinted the wrist in a neutral position, preventing discomfort from the exoskeleton and increasing cable efficiency. The final design was presented as the HOPE Hand

2.0. Additionally, orthosis customization was explored during a group project by using 3D Kinect scanning to generate parameters for SolidWorks parts.

5 Evaluation of Conventional Electromyography Device Control

Electromyography (EMG) is the study of the electrical signals produced by the muscle fibers (Konrad, 2005). While sensor technology has improved over the years to decrease signal noise, and algorithms have been used, varied, and invented, the basic information being gathered has remained the same. There are many applications of EMG: medical research, rehabilitation, sports science, and ergonomics. Prosthetic and orthotic devices are concerned with detecting neuromuscular activation using EMG sensors to direct the device movement, as a method of wearable assistance, and, in some cases, rehabilitation. There are two main approaches to analyzing muscle activity using EMG for the purpose of device control: a pattern recognition approach and a non-pattern recognition approach. Both approaches aim to detect movement intent or intentional muscle activation by implementing an intuitive user control strategy for enabling device users to operate a replacement or assistive limb structure.

5.1 Traditional Techniques for EMG Controlled Devices

A review of the current techniques for digitally processing myoelectric signals shows that there are many ways to manipulate the EMG signals to obtain information about muscle contractions, the state of the muscle, and so on (Hakonen et al., 2015). Conventional techniques consider time domain features, frequency domain features, time-frequently domain feature and spatial domain features of the myoelectric signal in order to identify a muscle event or condition. These features are used to study the signal properties such as amplitude and frequency. Time domain features are the most common in conventional techniques for identifying muscle contractions for wearable device actuation (Hakonen et al., 2015). This is because a wearable device should consider the myoelectric signals over a period of time to observe the sequential signal behavior.

Features of a myoelectric signal can be used in non-pattern recognition approaches such as onset analysis, and pattern recognition approaches such as feature classification.

A pattern recognition approach entails recording a signal, extracting certain features, and classifying that feature as an intention of a certain movement. This has been implemented in (Phinyomark et al., 2013; Meeker, Park, Bishop, Stein, & Ciocarlie, 2017) and quite a few more; gesture recognition is a popular area for research. Pattern recognition requires looking at a variety of features from multiple electrodes. Therefore, researchers place anywhere from four to sixteen electrodes around the circumference of the limb, allowing the sensors to record from multiple muscles at once. Different combinations of these features can allow the device user to accomplish a variety of hand positions. This approach does require more computation but can be intuitive for the user, especially if the user can accomplish different contraction patterns. A trans-radial amputee is a good candidate for the pattern recognition approach. Pattern recognition approaches require physiological differences in muscle activations in order to recognize intentional contraction patterns from all contraction patterns.

A non-pattern recognition approach refers to recording the signal and detecting the onset of intentional movement, which then triggers the actuation unit. There are multiple analysis methods for filtering data and identifying onset such as root mean square (RMS) and mean absolute value (MAV) which are moving average filters (Hakonen et al., 2015). These mathematical tools can be used to minimize the delay between offset and detection of offset, while maximizing the smoothness of the signal. Non-pattern recognition methods include onset detection and proportional (direct) control (Hakonen et al., 2015). Onset detection typically relies on setting a proper threshold which will be crossed during intentional movement, which can be very unsuccessful if the threshold is not set properly, or if the baseline muscle tone changes frequently. Because these control methods often act as switches, typically one electrode can be used to monitor one

muscle. In the upper extremity, common muscles to use are the flexor digitorum profundus, extensor digitorum, biceps brachii and triceps brachii. Direct control relies on muscle signals from an antagonistic pair of muscles to provide device movement at a speed or force proportional to the intensity or amplitude of muscle contraction. This control idea is designed to resemble normal neuromuscular activation and corresponding movements.

5.2 Conducting a Study

Hand exoskeletons have been developed to assist individuals with grasping and finger extension (See Chapter 2: Literature Review of Hand Exoskeletons). Once these devices have effectively accomplished the intended mechanical motion, the concept of control and the user interface is the next challenge. Ideally, this control method would be intuitive and robust. Within the last decade or two, companies and academic researchers have been using electromyography (EMG) to sense a user's muscle firings and activate the device movement based on the EMG signal. For amputees, EMG is a good option for prosthesis control, but individual's who have an intact limb, with a loss of function due to upper limb motor deficits, may struggle to produce the correct muscle activations required to operate an EMG controlled orthotic device. Because these motor deficits can present very different symptoms, EMG control might work for some, but there is still an under-served population, for whom EMG's might be difficult to use.

5.2.1 Purpose

An IRB approved study was conducted to evaluate conventional EMG control methods for their viability with a variety of muscle conditions, providing an idea of how many impaired individuals would be able to successfully use an exoskeleton controlled by EMG inputs with the conventional EMG technology and analysis. My hypothesis was that there will be a significant amount of subjects within the UMNS population for which existing EMG control methods would not be

a viable option for device control because of their unreliable muscle signals and unintentional muscle contractions. This prediction is based on interactions with individuals with unreliable muscle control as well as a study conducted in the winter of 2018 to measure the amount of force it takes to extend the fingers of individuals with a resting closed hand posture due to a traumatic brain injury. When the individuals were asked to extend their fingers, the muscle tone in their hand increased, causing the necessary force for extension to increase with a wider variety of performance (Nycz, Meier, Carvalho, Meier, & Fischer, 2018). This increase of tone could be recorded by EMG sensors, although an increase in tone is not directly correlated to the individual attempting to extend their fingers. The same increase in tone can be caused by walking/physical activity, increasing an individual's cognitive load or even emoting. The results from this study have informed the need for future development in EMG technology and analysis techniques.

5.2.2 Subjects

This experiment was conducted on nineteen subjects. Ten able-bodied subjects were recruited, as students of WPI and faculty and staff of Pine Bush Physical Therapy, to be the control group, to obtain information on the effectiveness of the EMG control methods on volitional muscle control. Nine impaired subjects were recruited, as referred to us (or approved) by a physical therapist from Pine Bush Physical therapy, to be the testing group. The impaired group included individuals that have positive symptoms and negative symptoms (Ivanhoe & Reistetter, 2004), due to UMNS, with varying levels of upper limb muscle control. Two of the impaired subjects have essential tremors, one subject has dystonia, four of the subjects have traumatic brain injuries, one subject has spinal cord injury and one has lack of function in her hand from Lyme disease (Fig. 30). All of the impaired subjects were chosen by the physical therapists because she believes they would be candidates for a hand exoskeleton or other assistive device for the hand/arm.

Both the able-bodied and impaired subject groups contained subjects from ages 21 to 78 in order to equally diversify the groups. There was an equal number of male and female participants in both groups.

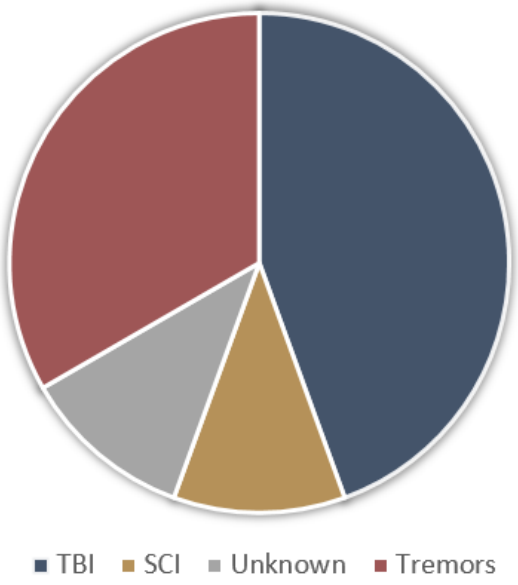

Figure 30: Causes for upper limb motor deficits within the impaired subject testing group

5.2.3 Set-up

Prior to arriving at the testing site, participants were asked to wear a short sleeve shirt or tank top so that the electrodes could be placed on the skin without undressing. Upon arrival the subjects were introduced to the study and subject consent was given. The skin was prepared for optimal sensor adhesion according to the following procedure suggested by the sensor manufacturers. If necessary, an investigator used a disposable razor to remove hair in the area where the sensor was to be placed. A new razor was be used for each patient. An alcohol wipe was used to clean the skin surface and pieces of scotch tape was used to remove excess skin cells and dirt which can build up on the skin surface, impeding the sensor readings.

A maximum of eight wireless Delsys, Inc. Trigno Avanti EMG electrodes (Fig. 31) were placed on the subject's upper extremity during the experiment using a

double sided adhesive tape which comes from the electrode manufacturer and is designed for skin use (Fig. 32). The surface of the electrode lays flat against the skin surface which allows the four conductive bars to measure electrical signals on the skin surface. The position of the electrodes will be dictated by the position of the muscle being recorded, and will be moved several times throughout the experiment. The data will be recorded on a laptop using software also created by the electrode manufacturer. The participant will be electrically isolated, as the electrodes will be powered via internal batteries and communicate wirelessly with the sensor base. The EMG signal bandwidth is 20-450 Hz and the sampling rate of data collection was 1111.11 Hz per one second. The ADC rate and resolution was not specified in the Delsys Trigno Avanti user guide or specifications.

Figure 31: Delsys, Inc. Trigno Avanti Wireless Electromyography sensor, Dimensions: 27 x 37 x 13 mm

The equipment set up for this study required a Delsys sensor base connected to a laptop running EMGWorks Analysis (data collection software from Delsys) and the Delsys trigger module. The Delsys trigger module was connected to an Arduino, which was connected to another laptop running the picture prompting. By connecting the Arduino to the Delsys Trigger Module, the picture prompting was synchronized with the start and stop buttons in EMGWorks. Figure 33 is a photo of the set up, including the equipment, and the skin preparation items.

Figure 32: Sensor with adhesive tape for skin adhesion

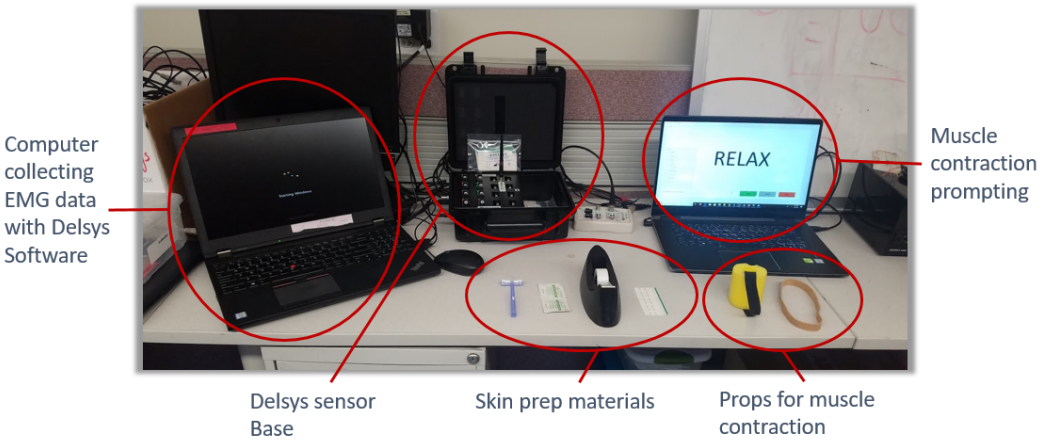

Figure 33: Equipment set up for EMG Study

5.2.4 Experimental Protocol

The study purpose and protocol was explained to each subject upon arrival and then each subject was asked to read and sign a consent form which has been approved by the WPI IRB. The sensors were paired and the age, gender, and race were documented to ensure the experimental subject group and the control subject group were equally diversified. EMG data was collected using the dominant hand for control subjects and the more impaired hand for the impaired subjects.

The experimental protocol was broken down into three parts: individual muscle sensing, forearm muscle sensing with six to eight electrodes in a band configuration, and upper arm muscle sensing with six to eight electrodes in a band configuration. For each of those parts, four data sets were collected: constant resting/force contractions, a training data set, a testing data set, and a real world based testing data set (Fig. 34).

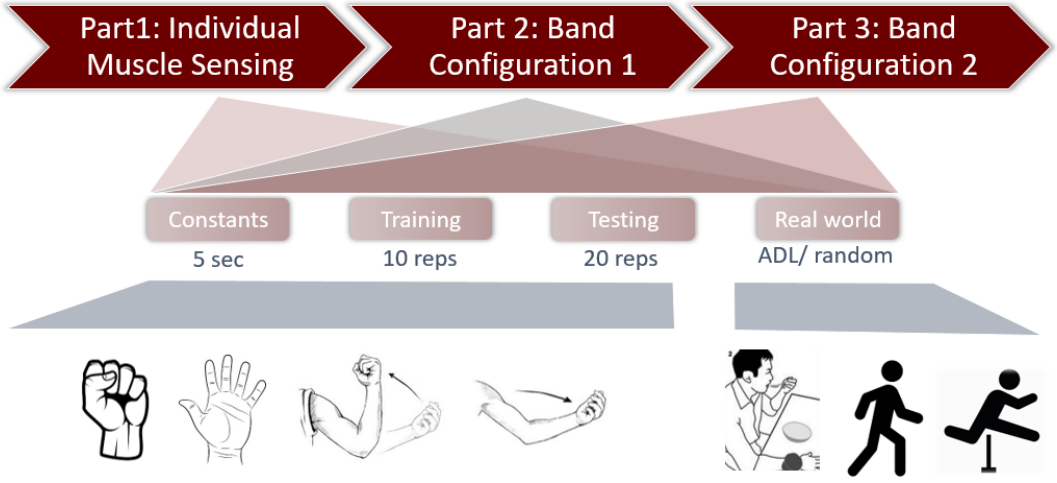

Figure 34: Electromyography study work flow broken down into three parts, each containing constant, training, testing, and real world data sets

For Part 1, four sensors were are placed on the arm. By knowing the anatomy of the arm, and by palpating the muscles, I was able to place each electrode approximately one centimeter distal from the muscle belly center. The four muscles that were recorded were the flexor digitorum profundus, extensor digitorum, biceps brachii, and triceps (Fig. 35).

Prior to data collection, each subject was instructed to contract 70% of their

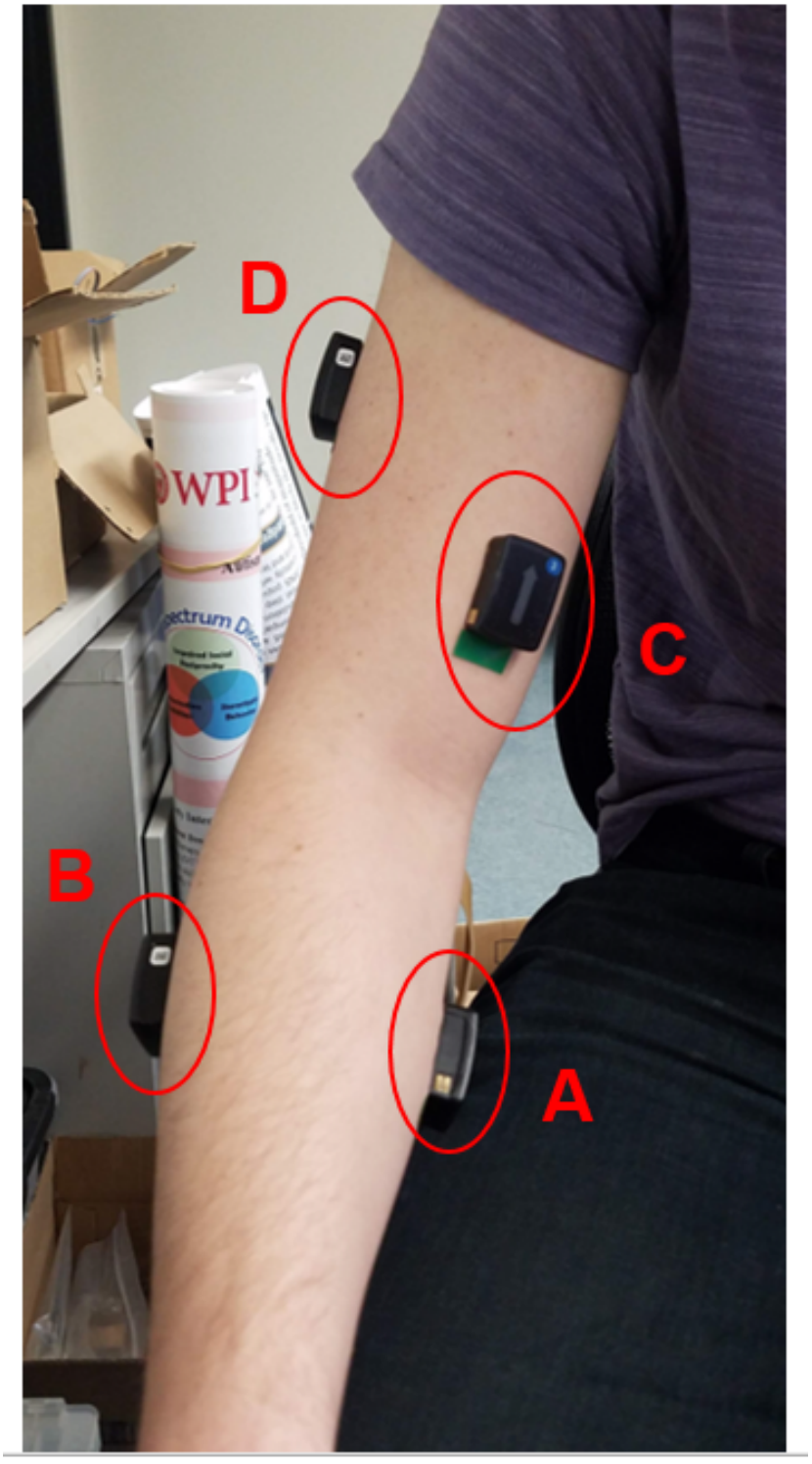

Figure 35: Sensor placement for Part 1 (individual muscle sensing) A) flexor digitorum profundus B) extensor digitorum C) biceps brachii D) triceps brachii

total contraction strength when given the contraction prompt. In order to regulate these contractions without sensing force, props were used for each dynamic contraction. Forearm flexor dynamic contractions were done by squeezing a poodle noodle. Forearm extensor dynamic contractions were done by spreading the fingers wide open. Biceps dynamic contractions were performed with a resistance band. Triceps dynamic contractions were performed by extending the arm against the chair armrest or the subject's inner thigh.

A resting measurement was taken for ten seconds, followed by a constant contraction for five seconds from each of the four muscles. Next the subject was prompted to contract each muscle ten times, with five seconds of rest in between five seconds of contraction. In Figure 36 you can see the MATLAB GUI used to prompt the subjects, allowing me to know when I should be expecting to see muscle contractions. The first ten contractions are the training set.

Figure 36: Graphical user interface (GUI) used for subject prompting

After ten contractions of each muscle, the subject is instructed to contract each muscle 20 times as prompted in the GUI. These contractions make up the testing set. To conclude this part of the experiment, the subject is given randomized commands forearm flexor or forearm extensor, or biceps or triceps. The order of the randomized commands were recorded. This data set is the "real world based testing data" because if someone were controlling a device using an antagonistic pair of muscles, it is important for the algorithm to be able to recognize the difference between flex and extend.

For Part 2 of the study muscle contraction data was collected from sensors configured in a band around the circumference of the forearm, aligning with the original placement of the forearm flexor and forearm extensor sensors (Fig. 37). Data was recorded during resting, constant flexion (squeezing), and constant extension (spreading fingers wide). For the training set, the subjects were instructed to perform 10 contractions, alternating between flexion (five seconds) and extension (five seconds) with rests (five seconds) in between. for the testing set, the subjects were instructed to repeat the same task 20 times. The real world data set was recorded while subjects performed Activities of Daily Living (ADL). The three ADLs were eating, walking, and walking over uneven ground (stepping) (Fig. 38). These were included to observe if any of the impaired subjects' muscles would contract uncontrollably in response to focusing on another task such as walking.

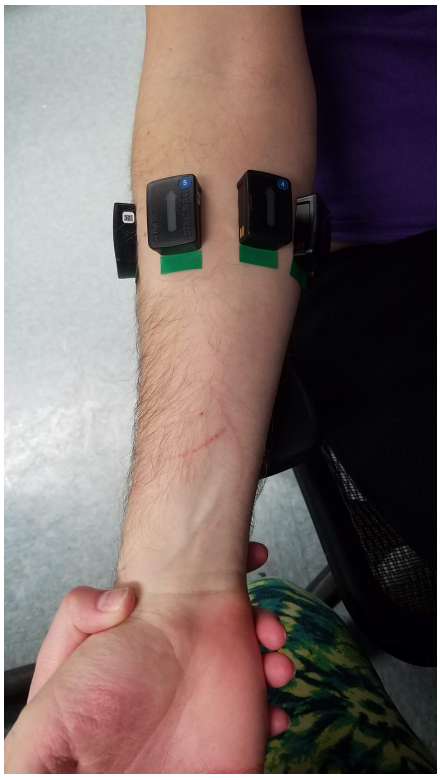

Figure 37: EMG sensors placed band configuration 1 which is when the sensors are placed in an array around the circumference of the forearm

For Part 3 of the study, the tasks from the Part 2 protocol was repeated, except configuration two (electrodes around the upper arm) was used, and the

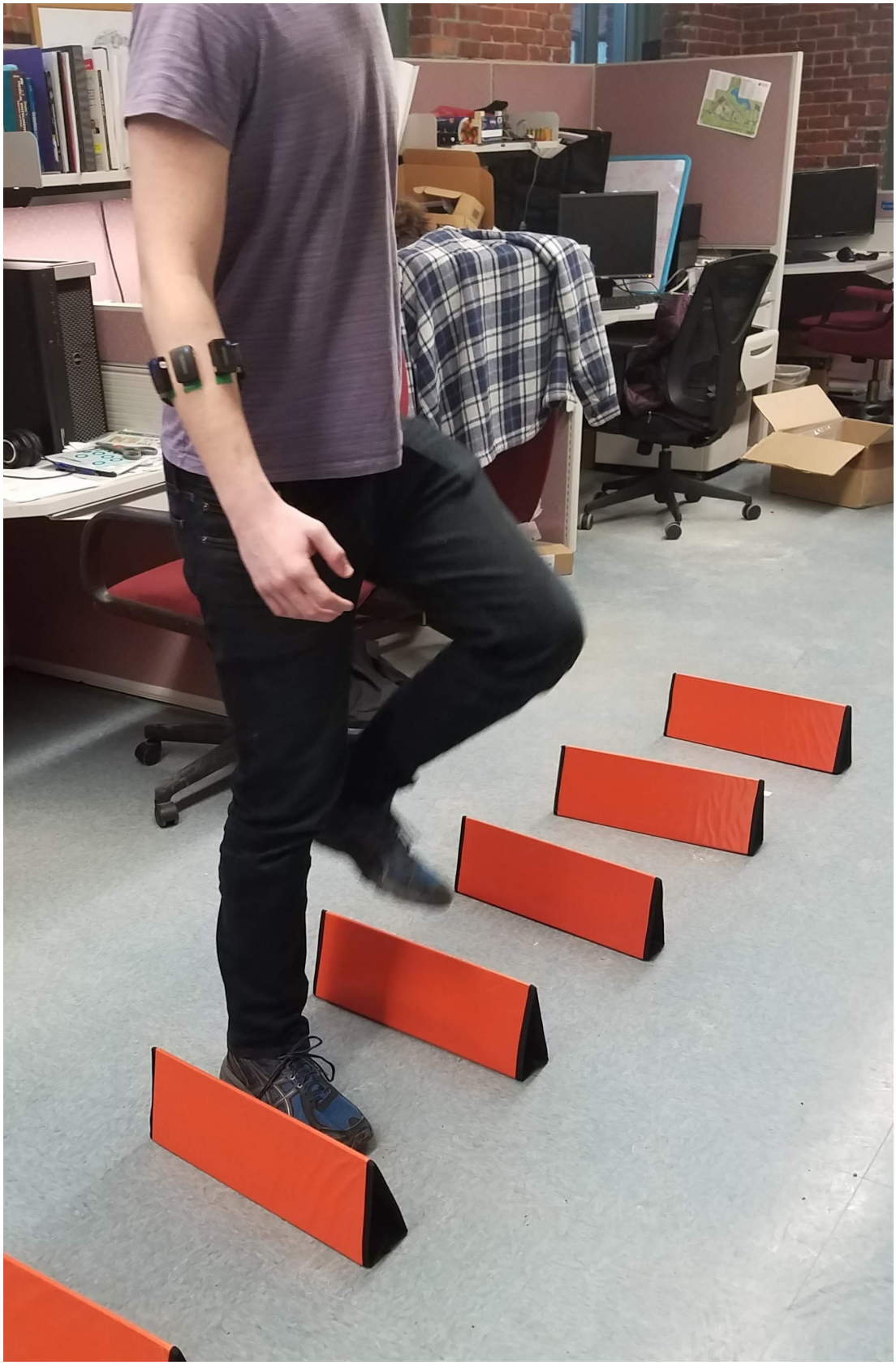

Figure 38: Able-bodied subject stepping horizontal cones which are size inches high, electrode band configuration 1 is shown around the forearm

subject was instructed to perform biceps flexion and triceps extension (Fig. 39). For both Part 2 and Part 3 of the study, the number of sensors placed around the limb was dependent on the circumference of the limb. For subjects with smaller limbs, six electrodes were used, for subjects with thicker limbs, eight electrodes were used.

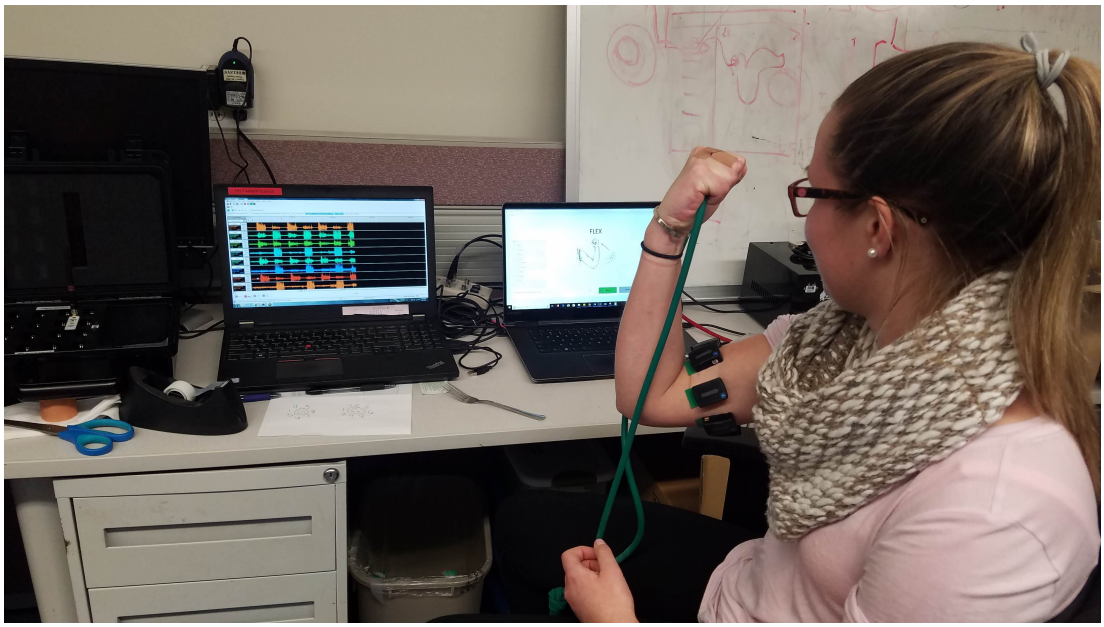

Figure 39: Able-bodied subject wearing sensors in band configuration two (electrodes in an array around the upper arm), while performing flexion as prompted on the screen (right), during EMG data collection shown on the screen on the left

5.3 Data Analysis Techniques

The EMG data was collected at 1111 samples per second from four to eight Delsys Trigno Avanti sensors. The reason for this odd sampling rate is because when the sensors are set to sample at 1000 Hz, the software or sensor base automatically increases that rate to 1111.11 Hz. From the raw data, time domain features were calculated to further process the data.

The features that were identified as being tools for data processing for this study were RMS, which is functionally identical to MAV, and waveform length (WL), which is the cumulative length of the waveform over the time segment (Hudgins, Parker, & Scott, 1993). Zero crossings (ZC), which is a measure of how

often the waveform crosses zero, and slope sign change (SSC), which is a measure of how often the slope of the waveform changes from positive to negative or vice versa (Hudgins et al., 1993), were also identified as potential features for use in data processing. These features were evaluated to identify muscle contractions for onset analysis and feature classification. MATLAB functions from an unpublished version of the EMG Amplitude Estimation Toolbox by (Clancy, 2004) were used to generate ZC, WL, and SSC features.

5.3.1 Onset Analysis

The EMG data collected from the four individual sensors during Part 1 of the study was used to evaluate onset analysis as a conventional EMG processing technique for assistive device control for impaired individuals. Onset analysis was implemented on each muscle individually, using data from a singular sensor. An overview of the onset analysis work flow can be seen in Figure 40.

The raw data sampled at 1111 Hz was filtered with a 10 Hz Butterworth high pass filter. Signals that have a frequency lower than 10Hz are typically due to motion artifacts. Then the mean squared value of the filtered raw signal was calculated with a window of 180ms (within the power domain). The window of 180ms was used because it falls below the perceivable delay limit of 250-300ms (Englehart, Hudgins, et al., 2003). To remove any resting noise offsets, the 10th percentile of data was average and subtracted from each signal value. The 10th percentile was used because the points which fall into the 10th percentile lowest amplitudes should represent the baseline of the EMG signal. After this subtraction, the square root was taken, returning the RMS filtered EMG amplitude.

In order to identify intentional contractions from the RMS signal, two thresholds needed to be set to account for signal hysteresis. The lower threshold was set at approximately .15 times the maximum value of the RMS signal and the upper threshold was set at approximately .3 times the maximum values of the RMS signal threshold. When the signal crosses the upper threshold, a counting

algorithm marks that time in the data as a contraction. In order for the algorithm to identify another contraction, the signal must first fall below the lower threshold. In the real world, the prothetist/orthotist would manually set the thresholds based on the user's repeated "training" contractions.

When both threshold were set, the counting algorithm was used to count how many times a contraction was identified and where in the time series it was identified. If the counting algorithm correctly identified the 10 intentional contractions, then the thresholds were exported and used with the testing data set (20 contractions) to evaluate how many contractions would be correctly identified. If the counting algorithm did not correctly identify the 10 contractions from the training set, the RMS window of 180ms was increased (up to 540ms in the worst case), the threshold multipliers were tuned, and, in cases of variable resting noise, the 10th percentile noise removal was increased (up to the 30th percentile in the worst case). Once these parameters yielded 10 correct contraction identifications, the thresholds were exported and used with the testing data. If the counting algorithm still failed to identify 10 contractions in the training set with, the parameters were tuned to get as close to 10 as possible. False positives, false negatives, and true positives were reported for the training and testing data sets, as well as the accuracy.

5.3.2 Feature Classification

The EMG data collected during Part 2 and Part 3 of the study was used to evaluate feature classification as a conventional EMG processing technique for assistive device control for impaired individuals. The work flow of this analysis process can be seen in Figure 41.

The raw data, sampled at 1111 Hz per second was recorded from six to eight EMG sensors which were located around the circumference of the arm while recording. The following features were calculated from the raw signal: RMS with a window of 360ms, waveform length (WL), and Zero Crossings (ZC). Those

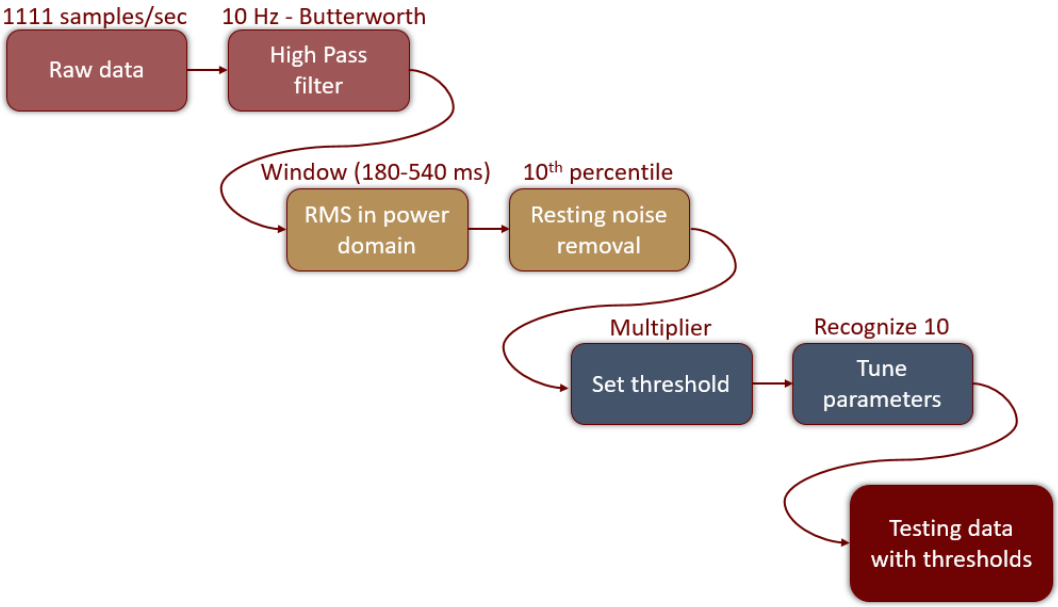

Figure 40: Work flow process for EMG onset analysis technique

features was calculated using the data from each of the sensors. Depending on how many sensors were used on the subject, there were between and 18-33 features. These features were used to train a classification model.

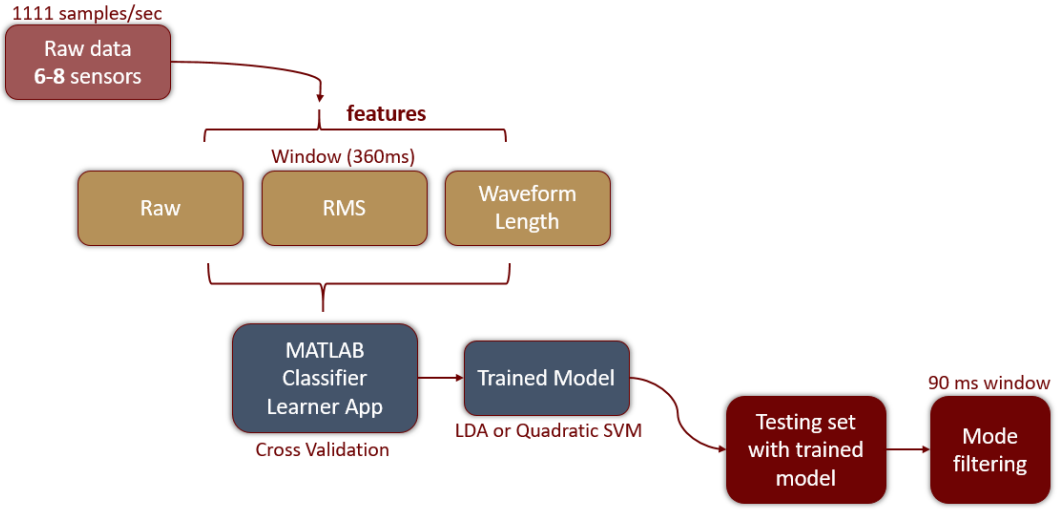

Figure 41: Work flow process for EMG feature classification technique

In order to prepare the training data set for the classification model training process, I automatically segmented the training data to cut out the transitions in between states, such as the transition from rest to flexion. This was done ensure that the generated response vector was associating the correct actions with the

correct labels. The response vector was auto-populated with three states: 0 = rest, 1 = flex, 2 = extend. The features and the response vector were then loaded into MATLAB's Classification Learner App (Fig. 42). Linear discriminant analysis (LDA) and support vector machine (SVM) are the most commonly used classification techniques for EMG data processing (Hakonen et al., 2015). The SVM had a manual kernel size of (sqrt(# of predictors)*4) as recommended by MATLAB. After both LDA and SVM were trained, the model with the higher five fold validation training accuracy was exported. Typically the SVM had a higher accuracy number within the training set's automatic validation. This could be an indication of over-fitting the data. If the accuracies were close or identical, I looked at the confusion matrix, also generated by the MATLAB Classification Learner App, which is a visual representation of the false positives and true positives that have been classified (Fig. 43). The model with the fewer false positives was chosen and the exported model was used to test the testing data.

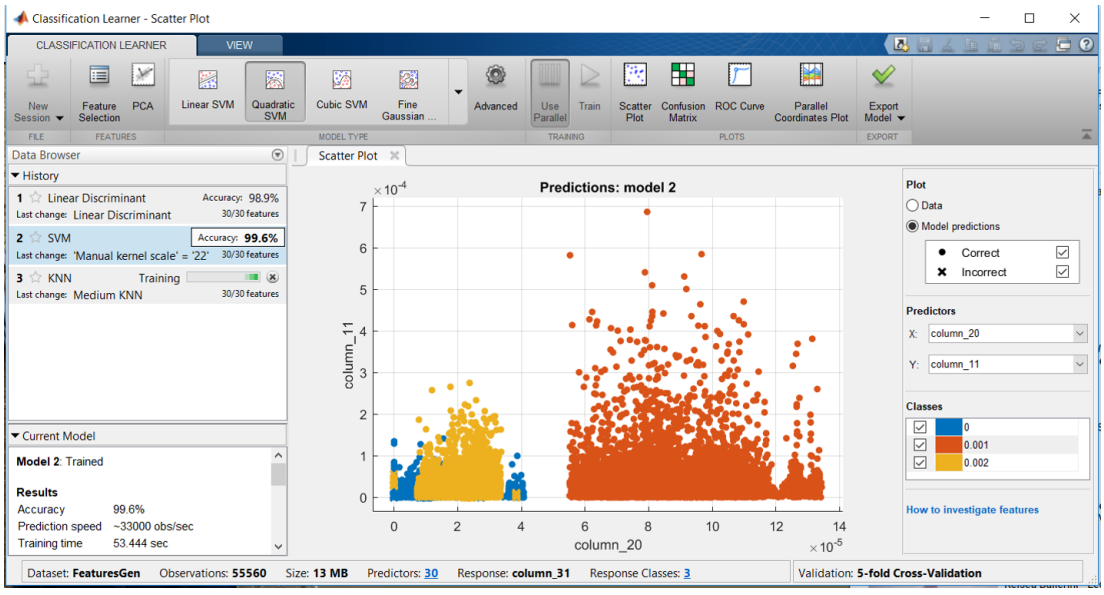

Figure 42: MATLAB Classification Learner App for Training EMG data using linear discriminant analysis and support vector machine

The testing data set was used to calculate a feature vector with the same features from the training set. The model was applied to the testing set predictors and a vector of the state classification at each time point was generated. This vector was filtered using by replacing the current value in the vector with the

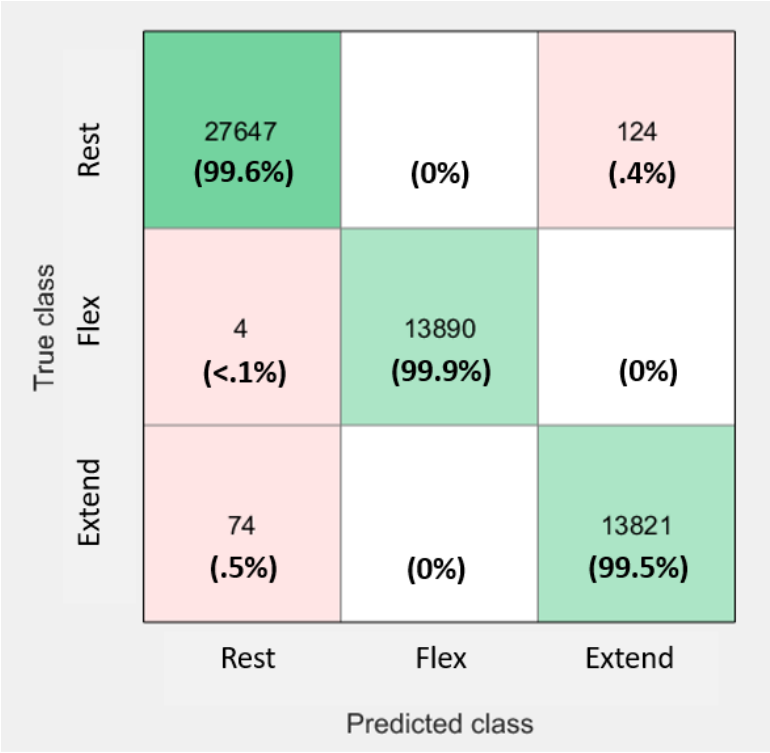

Figure 43: Confusion matrix representing correct classifications and false classifications as percentages; each row adds up to 100%

mode of the last 100 values in the vector (Fig. 44a). The filtered state predictions vector was evaluated with the counting algorithm that looked at which state was identified and when, in order to evaluate the ability of the trained model to recognize intentional contractions. The identified commands are shown in Figure 44b.

False positives, false negatives, and true positives were reported for the training and testing data sets, as well as the accuracy.

5.4 Study Results

EMG data from 19 subjects was collected and processed to obtain results and provide an estimation of how many impaired individuals would be able to use EMG as a reliable device control method. There were observations made about the muscle behavior of the impaired subjects. The data was processed using the onset analysis technique and the feature classification technique.

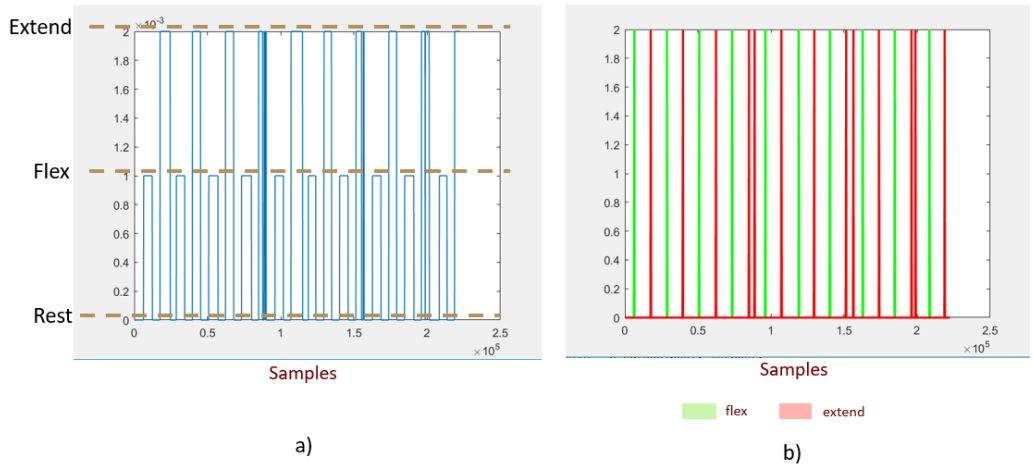

Figure 44: Visualization of the classifications made by the trained model when subject performed alternating flexion and extension in Part 2 and 3 a) state classifications from the testing data b) after a counting algorithm identified each contraction as a flex or extend

5.4.1 Observations

While the data was being collected during the experiment, there were observations made to preliminary assess the muscle behavior of the subjects. Co-contractions were frequently observed within the control group and the testing group; when the prompt instructed the subjects to dynamically flex their biceps in Part 1 of the study, the forearm flexor and extensor, and the triceps contracted simultaneously. In this scenario, if a healthy subject was contracting their biceps, there was an obvious change in amplitude of the EMG signal, while the other muscles co-contracting were large in amplitude as well, or smaller. This was not the case for one of the impaired subjects. Figure 45 shows an impaired subject contracting her biceps repeatedly (B); the muscle activity in her biceps was very minimal compared to the signals from the co-contracting muscles (E, T).

The subject's physical movement was observed during this experiment as well, and her biceps contractions were the only contractions resulting in physical movement of her arm, even though they appeared to be less active electrically.

The next observation was made from a healthy individual's alternating biceps/triceps data set from Part 3 of the study. Figure 46 shows an alternating pattern, making a clear distinction between biceps contractions, triceps contrac-

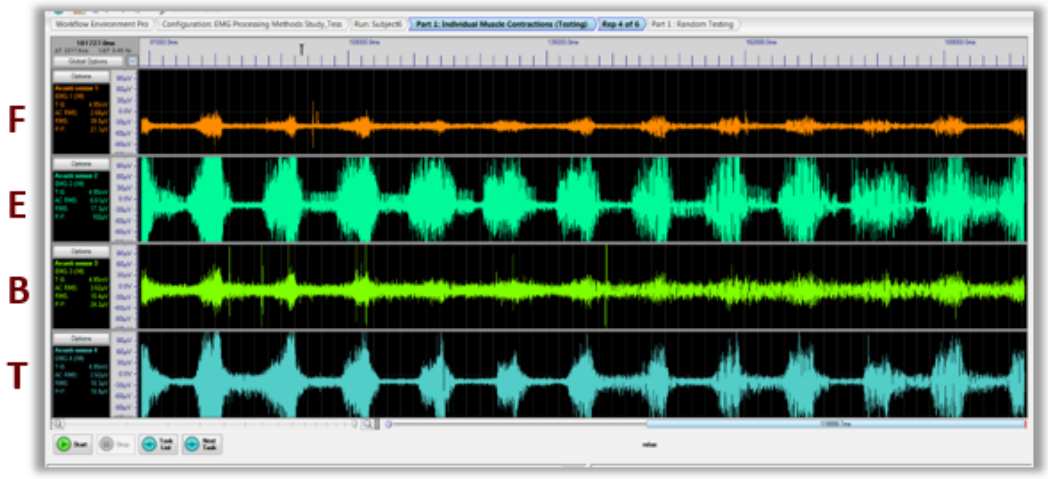

Figure 45: Impaired subject: 12 biceps contractions from Part 1; F = flexor digitorum, E = extensor digitorum, B = biceps, T = triceps

tions, and rest. This data was collected using an array of six to eight electrodes around the circumference of the upper arm. The orange signal on the top of the image is EMG data from an electrode that was placed on the bicep; the signal clearly is stronger when the subject is contracting their bicep. The mint and blue signals (fifth and sixth from the top) were showing data from an electrode that was placed on an extensor muscle of the upper arm, as they show activation during extension only. Some of the electrodes were placed such that they picked up activation signals from elbow extensor and flexor muscles, such as the lime green and red signals (third and seventh from the top).

A third observation was gleaned by looking at the data shown in Figures 47 and 48. In Figure 47 a impaired subject was instructed to contract their flexor muscle by squeezing the pool noodle in Part 1 of the study. The flexor digitorum (F) shows very little activation but the extensor digitorum (E) shows significant activation. Then looking at Figure 48 we see an impaired subject with a similar impairment, instructed to contract their extensor digitorum by spreading their fingers wide, opening the hand, and no activation was seen in the extensor muscle. This seemed to be a consistent observation of the impaired subjects with TBI; when they attempted to perform finger flexion, their finger extensors showed more activation, and when they attempted to perform finger extension, their finger

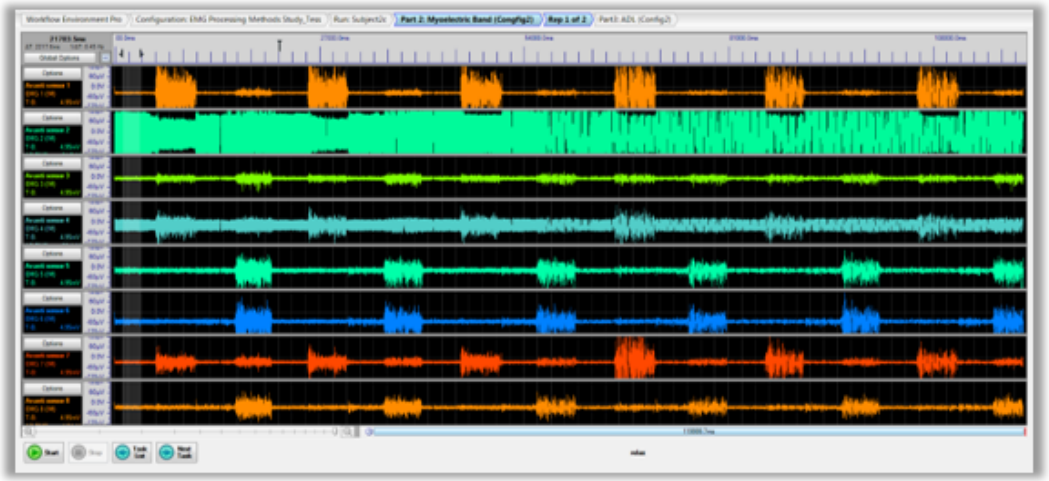

Figure 46: Healthy subject: alternating biceps/triceps contractions from Part 3; the first trace at the top (orange) shows electrical activity when the individuals is performing biceps flexion; the 5th, 6th, and 8th traces show electrical activity when the individual performs triceps extension

flexors showed more activation. Observation of the impaired subject's physical movement showed very little to no physical movement in the hand in flexion or extension. If a finger flexion motion occurred, it was due to an increase in muscle tone triggered by attempting to extend their fingers.

From these observations, it is clear that the impaired muscle conditions, were counter-intuitive, unpredictable, and complex. It was rewarding for the impaired subjects to visualize what their muscles were doing, because it is frustrating to try so hard to move your limb without seeing it actually move. Even though there was little physical movement of the limb, these subjects could see that their muscle and the signals were still activating, the neural pathways are still intact, they are just not fully accessible for intentional and reliable movement.

5.4.2 Onset Analysis Results

The data analysis technique described in Section 5.3.1 was used to process the healthy and impaired data from Part 1 of the study. The contraction from each of the four muscles (flexor digitorum, extensor digitorum, biceps, and triceps) were processed individuals with unique threshold for every muscle, for every per-

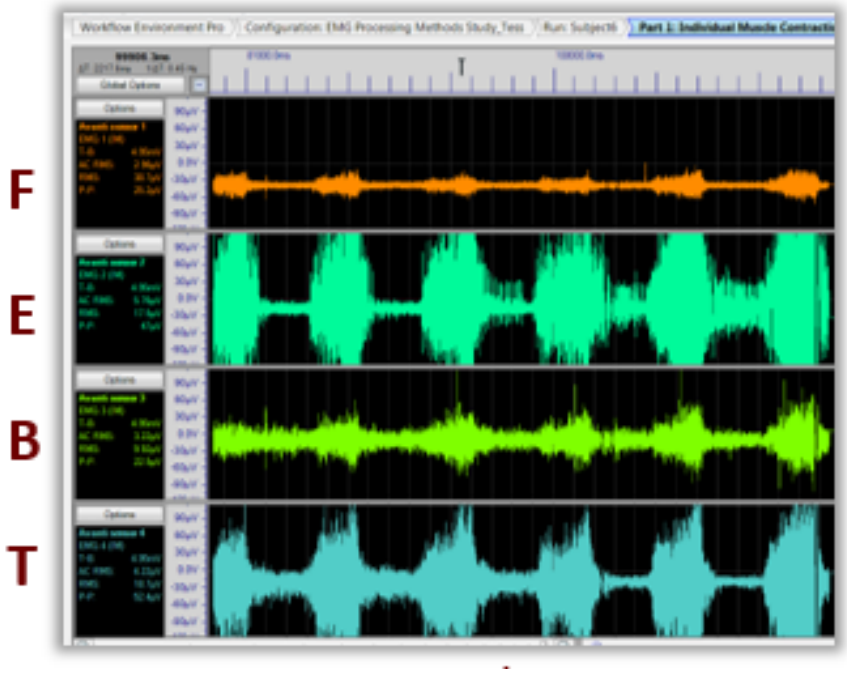

Figure 47: Impaired subject: 6 flexor contractions from Part 1; F = flexor digitorum, E = extensor digitorum, B = biceps, T = triceps

Figure 48: Impaired subject: 5 extensor contractions from Part 1; F = flexor digitorum, E = extensor digitorum, B = biceps, T = triceps

son. The total number of prompted training contractions across all four muscles was 40; in Table 2, the first true positive (TP) column on the left, represents the average number of contractions identified out of 40 for healthy subjects and impaired subjects. The true positive (TP) column on the right of the table, is the average number of contractions identified out of 80 (20 contractions for each of the four muscles) for healthy and impaired subjects. The table shows a trend of decreased TP and increased FP and FN for impaired subjects, whereas healthy subjects had an average near 100% accuracy with very few FP and FN.

Table 2: Onset Analysis Results

	Training				**Testing**			
	TP	FP	FN	Accurac	TP	FP	FN	Accuracy
Healthy	40	.3	0	99.3	80	2.8	0	96.7
Impaired	32.44	13.1	4.5	73.6	66.4	25.8	8.4	73.6

TP = true positive, FP = false positive, FN = false negative

The accuracy was calculated using the equation 1 below from (Englehart et al., 2003). The average accuracy of the onset analysis technique for identifying intentional contractions is 96.7% for the control group and 73.6% for the impaired group.

$$\textbf{Accuracy} = \frac{numberofcorrectclassifications}{totalnumberofclassifications} \quad (1)$$

The accuracy for each subject gives us a better understanding of how many subjects might be successful using this EMG control technique. For the purpose of my analysis in this thesis the accuracy for each subject was categorized, based on subjective discrimination of the results and observations from literature and user studies. Subjects with an accuracy of 90% or higher are deemed to be successful with EMG control. Subjects with 80%-90% accuracy may be successful with further training. Subjects with less than 80% accuracy would really struggle. For healthy subjects, 100% had an accuracy over 90%. For impaired subjects, 11% (one subject with SCI) had an accuracy over 90%, 22% (two subjects with

tremors) had an accuracy between 80%-90%, 55% (one subjects with tremors, three with TBI, one with unknown) had an accuracy between 60%-80% and 11% (one subjects with TBI) had an accuracy below 60%. Table 5 shows the average accuracy per impaired condition which suggests which injuries/conditions may be better suited for an EMG controlled device.

Table 3: Average Accuracy of each Impaired Condition using Onset Analysis to Identify Contractions

Condition	**Accuracy**
SCI	95%
Tremors	82%
Unknown	69%
TBI	62%

According to these results, EMG control, using the onset analysis technique implemented for this experiment, would be a viable option for three out of nine impaired subjects.

5.4.3 Feature Classification Results

The data analysis used in Section 5.3.2 was used to process the healthy and impaired data from Parts 2 and 3 of the study. The alternating contractions from the forearm flexors and extensors, and the biceps and triceps, were processed as two separate data sets for each individual, with a feature vector of RMS, WL and the raw signal. Typically the raw signal is not used as a feature which will be discussed later in the discussion section. The total number of testing contractions for each muscle was 10. In Table 4 the TP values represent the average number of contractions identified out of 10 for each muscle, within the healthy subjects and the impaired subjects. The TP values for the healthy subjects was closer to 8 out of 10, whereas, the impaired population TP averaged 5 or 6 out of 10. The healthy subjects had significantly less FP and FN, as the highest FP value for healthy subjects was and average of 3.1, and the highest value for impaired

subjects was 13.7 which is more contractions than the 10 that were actually instructed (and identified). For example, a subject only performed the instructed 10 contractions, but the analysis indicated 23 contractions. These false positives are an important point of discussion because they can be taken into account depending on the device control strategy. The accuracy for the healthy subjects and impaired subjects was calculated using equation 1. The average testing accuracy for healthy subjects was 83.4% and the average accuracy for impaired subjects was 49.4%.

Table 4: Feature Classification Results

	F			**E**			**B**			**T**		
	TP	FP	FN	TP	FP	FN	TP	FP	FN	TP	FP	FN
H	6.8	1.3	3.1	9.2	.4	.7	8.1	3.8	1.9	8.8	3.1	1.4
I	5.2	5.7	4.2	5.3	4.8	4.2	5.8	13.7	4	7.3	6.1	3

H = healthy, I = impaired, F = flexor digitorum, E = extensor digitorum, B = biceps, T = triceps

The accuracy for each subject gives us a better understanding of how many subjects might be successful using the feature classification method I implemented. For the purpose of my analysis in this thesis the accuracy for each subject was categorized. The accuracy I suggest to indicate successful use is above 70%. This is taking into account the baseline accuracy of the healthy population. If that average value were to be improved to near 100%, I am making an assumption that the impaired subject's accuracy would scale accordingly (this may not be the case). Only 22% of the impaired subjects had an accuracy over 70%. This suggests that 78% of the impaired individuals would struggle with operating a device using the feature classification method implemented within this study. Once again, the average accuracy per condition was summarized in Table 5 to show trends in condition type.

Table 5: Average Accuracy of each Impaired Condition using Feature Classification to Identify Contractions

Condition	**Accuracy**
SCI	76%
Tremors	46%
Unknown	36%
TBI	51 %

According to these results, EMG control, using the feature classification implemented for this thesis work, would be a viable option for two out of nine impaired subjects. Direct comparisons of accuracy between these implementations of onset analysis and feature classification cannot be made because feature classification involved identifying three states (open, close, rest), while onset analysis involved identifying two states (action, rest).

5.5 Discussion and Future Work

By combining the results from the onset analysis and the feature classification, four impaired subjects are likely to be successful using a device controlled either by onset analysis or feature classification. Based on the metrics for success previous noted, for the specific algorithms and sensor configurations evaluated, 55% of the impaired subjects would not be very successful using an EMG controlled device with onset analysis or feature classification.

While I believe the results suggest the capabilities of EMG as a control mechanism, there are causes of error that should be discussed. With any surface EMG testing, skin condition plays a large role in signal quality. By removing oils on the skin with an alcohol wipe, and shaving arm hair (if necessary), I was able to obtain high quality signals, but skin condition remains to be a variable. Placement of the sensors is another variable that will greatly affect the quality of the signal. Palpation of the muscle is a fairly robust way of placing the electrodes

but with patients who are elderly, excessive skin becomes an issue because fat and skin in between the muscle and the sensor will dilute the signal.

Another challenging component of EMG analysis for understanding muscle contractions and the resulting physical movement is co-contraction. It proved to be very hard for most of the subjects, including the able bodied control subjects, to isolate their muscle contractions, even with instructions on contracting dynamically.

The results for the traumatic brain injury patients were very interesting. The average accuracy for TBI subjects using onset analysis was ranked to be the least successful impaired group at 62%, but for feature classification the average accuracy for TBI subjects was ranked second most successful impaired group. TBI subjects exhibit unique muscle behavior because their limbs showed very little movement but the muscles were contracting. It was common to see extensors active during flexion but when the subjects were asked to extend, there was little to no signal coming from the extensors. For some of the patients there were distinguishable differences between flex and extend using the band configuration. There are some topics for consideration: If an effective control algorithm recognizes the impaired person's intention, is it positive for the device to resist the increased muscle tone from the control contractions and possibly training the wrong muscles? Is it detrimental to use the opposite muscle for actuation because that might encourage pathways to reform incorrectly?

The subject with a SCI showed high accuracy in both onset analysis and feature classification suggesting this person would be a great candidate for an EMG controlled device. However, because they have strong and reliable muscle signals, even though their hand doesn't function normally, the subject is able to use the tendonesis effect to accomplish ADLs with his impaired hand. So we have to ask ourselves, would an assistive device be less helpful than the compensation technique the subject has already developed?

The individuals with tremors had an average accuracy that was in the mid-

dle of the pack for both data analysis techniques. The subject with the unknown condition exhibited success using onset analysis but did poorly with feature classification, which is opposite of the TBI patients, even though, based on the physical state of the hand, I would've predicted the unknown subject's results to trend with the TBI results.

Because these subject groups are very small, conclusions based on the larger population cannot be made. In fact, conclusions regarding each individual's ability to use EMG with the implemented techniques, can only suggest if that individual would be a good candidate for EMG control. In the future, conclusions could be made on the correlation between severity of disability and ability to use the implemented EMG control successfully.

Feature classification implementation success can change depending on the features used to train the classification model. I used RMS, WL, and the raw signal, from each of the sensors to create my feature vector. The raw signal is never used in feature classification because of its wildly variable values, however, when the raw signal was removed as a feature, the model got worse at predicting contractions. This could be a coincidence, and moving forward, raw signal should be removed from the feature vector. Another issue with my implementation of the features, is that I did not low pass filter all of the features. The WL feature would've been more helpful if I had filtered it because of its variable raw values. In future work, all features will be filtered prior to training the model.

Another point of discussion is how to handle false positives. Depending on the controller designed for the actual device control, some of the false positives within the testing results might not have been an issue. For example, Within the five seconds of biceps contractions, if the model detected two biceps contractions, that means that in between those two contractions, rest was identified, however If the control strategy only looks for contraction signals than the hand exoskeleton would see a second command for "close" and know that it was already closed, so it just wouldn't move. However, if rest was a gesture used to indicate a movement

command, then the device would switch from closed to relaxed/open to close with the second biceps contraction.

The accuracy values for the healthy subject group seemed low compared to the literature from (Hakonen et al., 2015). Figure 49 shows the reported accuracy values from various feature classification techniques from the literature. While most papers reported an accuracy of near 100%, there was one that reported values between 70% and 90% (Tkach, Huang, & Kuiken, 2010), which was more aligned with the results presented in this thesis for feature classification on healthy subjects.

This study by Tkach was looking at electrode conditions that might effect the accuracy, such as electrode location shift, contraction level change and muscle fatigue (Tkach et al., 2010). These results could be comparable to my results because my study was designed to mimic a real world context. My study had no test fixture used to ensure that every contraction and arm position was identical and there was no load cell used to ensure that each contraction was of the same level. The goal for my study was to evaluate EMG control for these impaired patients. Even though the experimental set up is also not perfectly modeled after the real world, it is the best case scenario. As in, the use of EMG control in the real world, would have variable conditions such as electrode shift, fatigue, and contraction level change. Therefore, if these subjects struggled to produce reliable muscle signals in a fairly controlled environment, the performance in the real world would be worse because of the aforementioned variable conditions.

Another possible explanation for lower healthy accuracy is motion artifacts. Taking a close look at the feature classification on the healthy subjects- specifically the Biceps/triceps trials, I noticed that a few of the classifications were particularly bad. Looking at the raw data, it was very clear to see when the person was contracting their biceps/triceps vs. when they were relaxing (Fig. 50: Sensor1). Upon further investigation, the sensors that were positioned on the inside of the arm were likely to have motion artifacts (Fig. 50: Sensor 7 & Sensor

Table 3
TD feature vectors used in sEMG interfaces. H = healthy subject, A = amputee subject. 1 = classification accuracy under electrode location shift, 2 = classification accuracy under muscle contraction level change, 3 = classification accuracy with muscle fatigue. CKML =Cascaded-kernel learning machine, SE = sample entropy, AR6 = 6th order AR coefficients.

Feature vector	Classifier	Classification accuracy (%)	Classes	Bipolar electrodes	Subjects	Reference
MAV, WL, ZC, SSC	SVM	96	6	4	11H	[93]
MAV, WL, ZC, SSC, AR6	LDA	97	10	3	12H	[7]
MAV, WL, ZC, SSC, AR6, RMS	GMM	97	6	4	12H	[125]
MAV, WAMP, VAR, WL	ANN	98	12	32	1H	[117]
MAV, WAMP, AR, CC	LDA	70^1, 78^2, 87^3	4	2	8H	[115]
MAV, WL, AR, CC	LDA	70^1, 78^2, 88^3	4	2	8H	[115]
WL, LOGDET, AR, CC	LDA	70^1, 78^2, 88^3	4	2	8H	[115]
SE, CC, RMS, WL	LDA	98	11	4	4H	[130]
IEMG, WL, VAR, ZC, SSC, WAMP	GRA	96	11	7	12H	[113]
AR6, MAV	LDA	98H, 79A	11	4	5H, 5A	[132]
AR6, ZC	LDA	97H, 75A	11	4	5H, 5A	[132]
AR6, SSC	LDA	97H, 74A	11	4	5H, 5A	[132]
AR6, WL	LDA	98H, 79A	11	4	5H, 5A	[132]
AR6, RMS	SVM	96	6	4	11H	[93]
AR, HIST	CKLM	93A, 97H	8	3	2A, 1H	[119]

Figure 49: A table compiled by (Hakonen et al., 2015) to show the accuracy of classification strategies in the literature (all references from table are not included). Most of the accuracy values are close to 100% although there are some in the 70%-90% range.

8). These motion artifacts may have been caused by the sensor bumping into the person's side when they released their dynamic contraction. It is possible that there was not good contact between the skin and the electrodes so motion and collisions made the motion artifacts more pronounced, such as Sensor 7 (Fig. 50). Further studies on positioning and motion artifacts would need to be conducted in order to confirm this theory. Controlling the arm movement and the forces the subjects are applying could decrease this effect. Additionally a high pass filter with a higher cutoff frequency could be used to filter the data.

Even though there were reasons for my healthy subjects having a low accuracy with feature classification, I wanted to investigate how to increase this accuracy.

One likely reason for misclassifications is co-contraction which happens at the beginning of the muscle contraction can look like the other state to the classifier. This can be seen in Figure 51. This causes the first group of data to be labeled as flexion when it might have been extension. There are a few ways this can be addressed. The first way is by adding a longer delay prior to declaring the state so there is more data points to be sure of the classification. Another way that this could be approached is by running multiple classifiers simultaneously and voting on which classification is correct.

Majority voting can also be used to determine the state, This involves looking

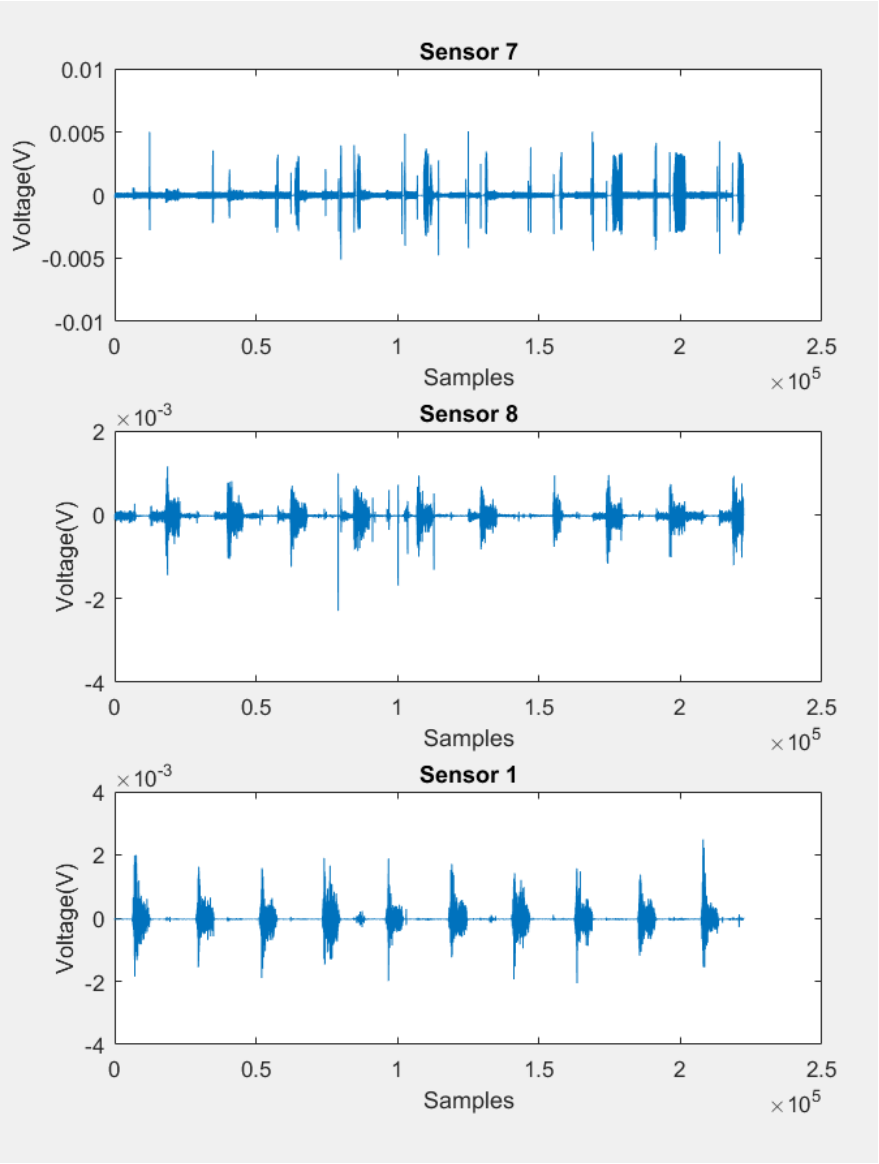

Figure 50: A comparison of the raw signal from Sensor 1, Sensor 7, and Sensor 8; Sensor 1 (on the biceps) shows very clear periodic contractions while Sensor 7 (under the arm) shows large amplitude more frequent spikes (motion artifacts as effect of collisions between sensor and body with poor electrode/skin contact) and Sensor 8 (under the arm) shows motion artifacts as well, to a lesser extent

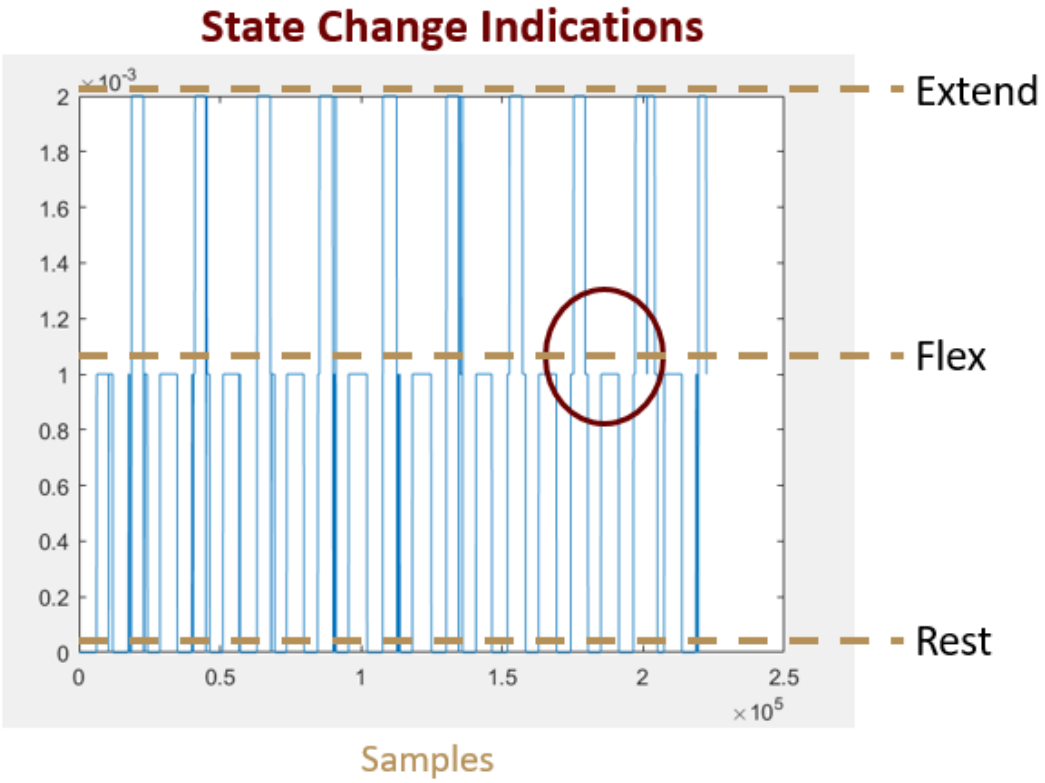

Figure 51: This graph shows state classifications from the testing data, inside the red circle, during an extension contraction the blue square wave stops at flex and then continues to extend causing the counting algorithm to identify the contraction as a flex instead of an extend.

a series of data windows and identifying the mode for each window, and then identifying the mode of all the windows together (Hargrove, Englehart, & Hudgins, 2007). This technique was implemented on data from one subject to see if it would have a significant effect on improving classification accuracy. This technique did not show any improvements for the singular subject data set but majority voting could be useful for other subjects.

Another technique for improving classification accuracy is a scheme by Scheme which involves using the LDA classifier model output to obtain the weights and offsets for each state to be used in two equations to calculate the confidence value of the state classification (Scheme & Englehart, 2015). The state change can either be accepted or denied based on how high the confidence value is. This technique has not been implemented currently but it would be beneficial to see if it would improve the accuracy.

Another avenue for accuracy improvement that I considered was changing the features I used. From the original feature vector containing the RMS, WL, and raw signal, I tried adding ZC; I tried removing raw signal; I tried using only RMS. A lot of these combination produced more false positives. So it was decided that false negatives were preferable over false positives justifying the use of the original feature vector. I also changed the time requirement in the counting algorithm which requires the signal to be the same for a longer period of time before classifying it. The longest delay tested was 1800ms, almost two whole seconds. This delay did improve classification results but it is not a practical amount of time to be used in device control.

While the data processing algorithms are designed to be used in real time, the delays for this study are significantly higher than what is typically seen in prosthesis control. Because this user group would not be able to move their hand otherwise, the delay might be acceptable because we are getting data that has the best potential, best case scenario.

My original thought for designing the study was to group parts of the ex-

periment by analysis method and the sensor configuration that was intended for that method. I would collect numerous contractions from one muscle, then set a threshold and do onset detection. Next I would collect classification data by putting the sensors in the band configuration- for which I would do feature classification for contraction detection.

Only after collecting approximately half of the subject data, did I realize that the structure of my data collection was not ideal. By doing all of the individual contraction with one sensor on each of the 4 muscles, then testing alternating motions with configuration 1 and configuration 2, I was moving the sensors around between each part of the study. Instead of the same data, looking at different sensors, I had a different contractions patterns which prevents me from making direct comparisons for the contraction identification techniques. By designing and conducting the study this way, I have limited myself in making comparisons of accuracy between methods.

Because my goal was to give an insight into how successful these individuals may be with EMG controlled devices, I feel the study was a success. One of my goals throughout the experiment was to mimic an actual users' environment, difficulties they may face like sensor noise, bumping the sensors on furniture or themselves. I have collected impaired subject data which can be used in the future to understand impaired muscle contractions and design new algorithms for this impaired population. The protocol I have established would be helpful in conducting further EMG studies.

5.6 Summary of Contributions

A study was design and conducted on 19 individuals, including nine impaired subjects, to evaluate the viability of conventional EMG methods for device control for a diverse group of impaired individuals. A significant contribution was collecting this data to now be used by the next group of researchers to try and design control methods based on EMG for impaired subjects who can't currently

use conventional EMG methods. Having data from impaired subjects will allow us to study, in depth, the differences between healthy muscle function and impaired muscle function. Conventional onset analysis and classification techniques were implemented for EMG device control, and it was determined that EMG control methods would be a great option for one out of nine of the impaired test subjects and approximately three others might be able to use conventional EMG control with further training. While this sample population is not large enough to make statistical claims about the population as a whole, these results provide insight as to the limitations of conventional EMG control methods and suggests there are a significant number of impaired individuals who would struggle with conventional EMG device operation.

6 Implementation of Three User Control Methods Performance of the HOPE Hand 2.0

In order to evaluate the final state of the hand exoskeleton, a second round of Box and Blocks testing was conducted with an impaired individual. The exoskeleton was donned by the subject and operated with three different user input methods. The first user input method was button control using a foot pedal. The second user input method was EMG control which was implemented as onset detection using a threshold. The third user input method was voice control with the verbal command "open" and "close". This final Box and Blocks testing allowed us to evaluate the performance of the mechanics on the HOPE Hand 2.0, as well as preliminarily evaluate each of the user input methods.

6.1 Patient Testing

The same 22 year old subject with hemiparesis due to a TBI was recruited for this second round of testing. Using the same subject provides continuity for the project and allows a direct comparison of results to be made, although it is important to note that the subject has made continual improvements throughout the year with her physical therapy, and also had botox injections approximately two an a half months prior to the second round of testing. Botox injections are used to relax the muscle and decrease hypertonia, and typically last six months (*Botox Treatment for Cerebral Palsy*, n.d.). According to her physical therapist, the botox injections decreased the muscle tone of her wrist flexors but not her fingers. Because of this, an assumption was made that her control trials of the first Box and Blocks Test, remained the same.

The testing process began with fitting the device to the subject. Much like the first time, the hand exoskeleton was brought to the testing site in pieces and assembled on-site. While the plastic pieces were generalized for a small sized hand, the lengths of the fingers, and the segment placement on the device is

crucial to performing a comfortable, safe, effective finger extension. Elastic strips were measured to the subject's finger lengths and the placement of her proximal guide and fingertip were marked on the elastic. The elastic was secured to the underside of the plastic finger components using liquid super glue. Once all of the finger segments were connected at the proper distance, black craft foam was glued to the underside of the plastic fingertips, with the elastic securely in between the foam and the plastic component (Fig. 25). The fingertips and finger segments were secured to the subject using medical tape and the cables were adjusted to the proper finger lengths (Fig. 52).

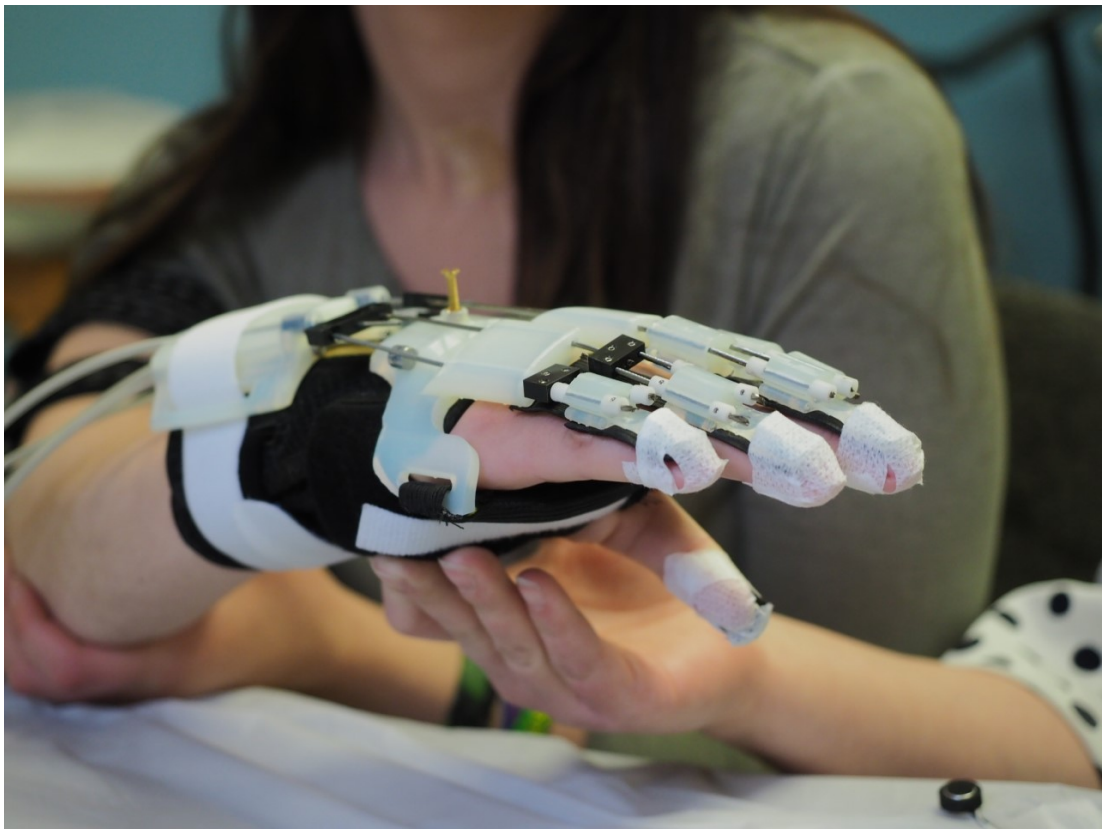

Figure 52: HOPE Hand 2.0 on impaired subject; taped fingertips secured the device on the user

6.2 Performance of Hand Exoskeleton 2.0

In order to evaluate the improvements made to the device, let us recollect the identified problems:

- Fingers were not able to fully extend

- Wrist was not stabilized
- Skin irritation and points of pressure
- Unable to perform functional grasps

The mechanics of the hand performed very well during this session of Box and Blocks testing. The fingertip tape successfully kept the device in place on the back of the hand while keeping the distal finger joint splinted, and there was little to no slippage in the joints. Because the fabric along the back of the fingers was replaced with elastic strips, the hand exoskeleton extended over the joints and contracted when the finger is extended, without bunching up. Therefore, the hand exoskeleton performed repeatable, full extension of the fingers.

The wrist was stabilized using the BraceUp, which immobilized the wrist in a neutral position. The BraceUp did cause some indentations in the skin from the stitching but those were the only marks left on the patient's skin from the device. The fingers were completely absent of marks (Fig. 53).

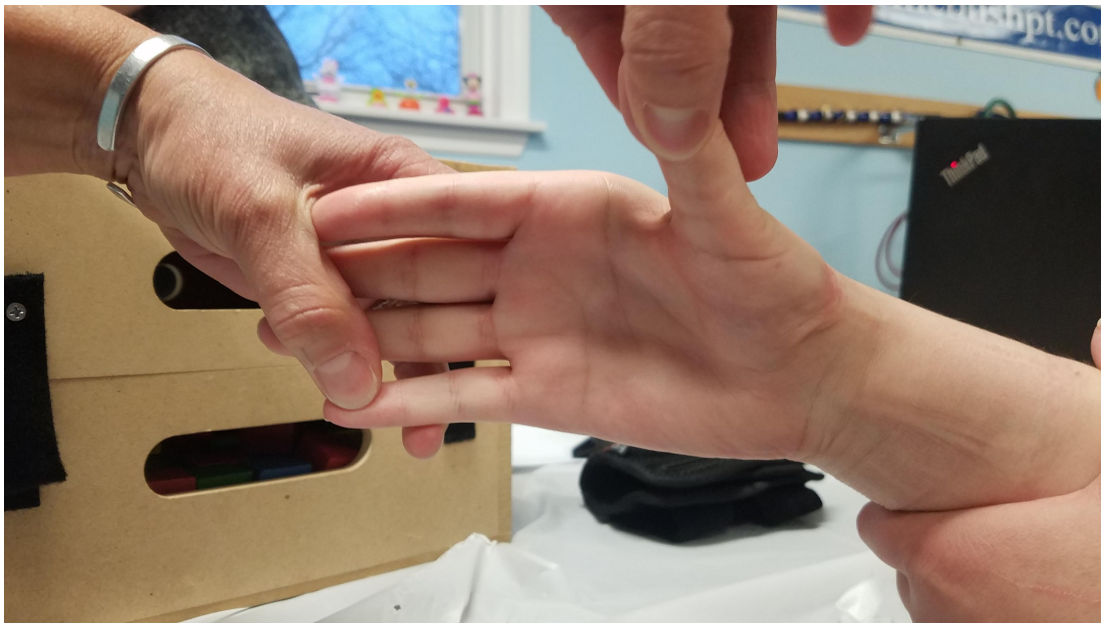

Figure 53: View of the palmar surface of the hand after appriximately four hours of wearing the HOPE Hand 2; no irritation marks on the fingers, mild marking around the thumb from wrist brace, barely visible marking on the forearm

Perhaps the largest success was being able to perform the three jaw chuck grasp with finger opposition by passively rotating the joint at the base of the

thumb and then actively changing the flexion/extension with the actuation unit. The pinky and ring finger were able remain extended and their coupled motion was natural.

6.3 Evaluation of User Control Methods

In addition to evaluating the revised mechanics of the device, three user control methods were implemented. After the subject donned the HOPE Hand 2.0, she trained for approximately five minutes using each user input method to open and close the hand, prior to completing the formal Box and Blocks test. The Box and Blocks test allows the subject 15 seconds of practice before the 60 second test (Fig. 54). The subject's results for each of the Box and Blocks trials are recorded in Table 6. The scores from the original trial are also included in the table for easy comparisons.

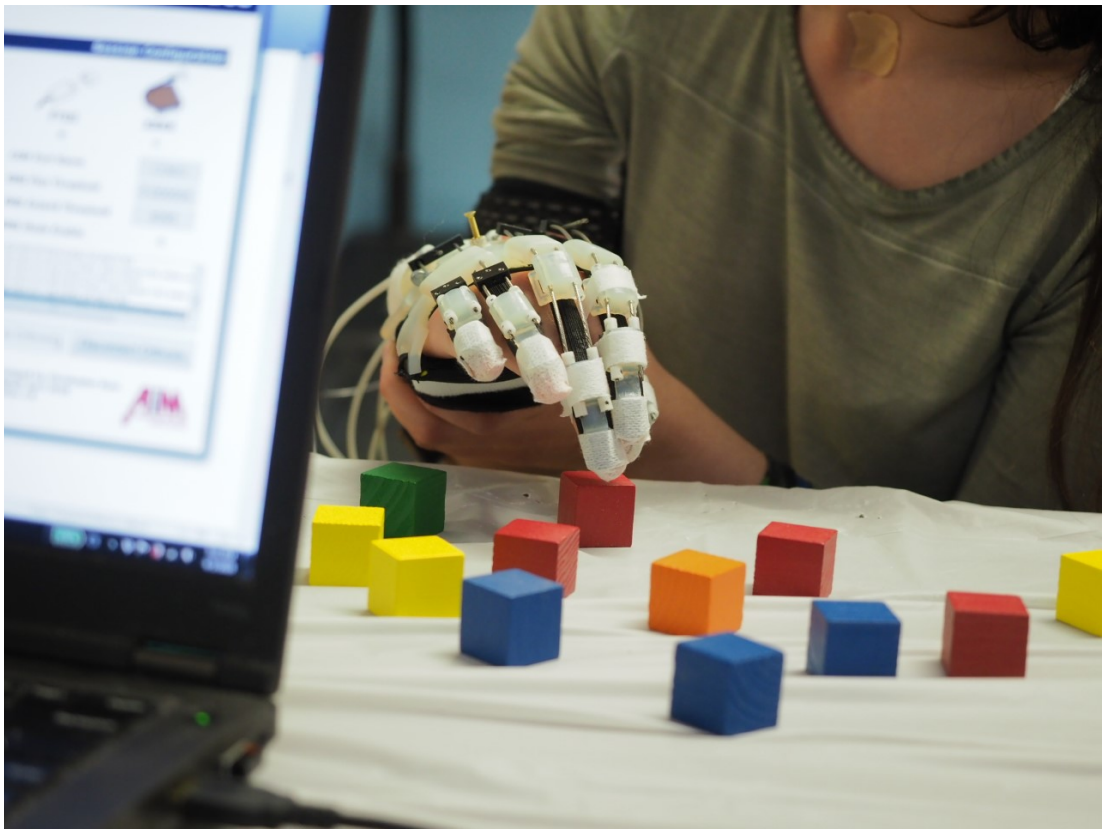

Figure 54: Impaired subject picking up blocks with the HOPE Hand 2.0 during a training session

Table 6: Box and Blocks with HOPE Hand 2.0

Test Condition	**Hand**	**Training**	**Testing**
Control 1 (from previous)	Sound	15	53
Control 2 (from previous)	Affected	0	0
HOPE Hand 1.0 (from previous)	Affected	Not Able	Not Able
HOPE Hand 2.0 Foot button	Affected	1	2
HOPE Hand 2.0 Voice commands	Affected	1	1
HOPE Hand 2.0 EMG commands	Affected	0	0

This study was conducted with the same impaired individual from the original Box and Blocks testing

6.3.1 Manual Control

Manual control with a button is a very common way for researchers to validate the functionality of their wearable assistive device (Polygerinos et al., 2015; Gasser et al., 2017; Kang et al., 2016). While implementing manual control is simple and reliable, it may be un-intuitive. Typically the button is integrated into the device for testing in a lab setting, where the button is on the table, and the user can press it with their sound hand, or its on the ground and they can press it with their sound foot. These implementations may require the subject to sacrifice the functionality of their sound sound in trying to perform with their affected side. Therefore, manual control might not be ideal or incredibly intuitive but it allows the user and the researchers to reliably test the mechanics of the device.

A foot pedal was implemented as a manual control option using an Arduino to interface with the hand exoskeleton control GUI. When the foot pedal is pressed, the Arduino pin reads HIGH, which signals the hand exoskeleton to toggle between the states of open and close. Because the subject uses her sound arm to position her affected arm, it would have been challenging for the subject to press a button with her sound hand. This is why a foot pedal was implemented instead. The subject stepped on the foot pedal with her sound leg when she wanted the

exoskeleton to close and open.

There was some difficulty with the foot pedal because the subject was seated and the button was intended to be pressed while standing, as it requires a substantial amount of force to be pressed. However, after mounting the foot pedal to the floor, the subject became more comfortable with using it and was able to move one block during the training round of the Box and Blocks test and two blocks during the testing round (Table 6).

6.3.2 EMG Control

The subject's arm was palpated while the subject attempted to close their hand. One Delsys Trigno Avanti sensor was placed on the subject's extensor digitorium because it produced the most reliable contraction during attempted finger flexion. The subject was asked "make a fist" which produced activity in the extensor muscle. The peaks of these contractions were observed and a threshold was set approximately between the resting signal level and the maximum signal peak. This threshold was tested and moved slightly until the subject's contractions reliably resulted in movement of the hand exoskeleton. Using the Delsys API, we were able to live-stream the data into the HOPE Hand control GUI. For each data package being sent from the Delsys base, an RMS filter was implemented to display a signal envelope which was used as a comparison against the set threshold. Throughout training and testing, the extensor muscle signals were monitored and when the subject contracted her extensor, the threshold was crossed and the hand exoskeleton toggled back and forth between open and close.

In both the training and testing sessions of the Box and Blocks test, the subject attempted to close the hand and open the hand by trying to "make a fist." She made several successful attempts at closing the fingers around the blocks in training and practice, but because of complications with residual extensor muscle tone increase, the hand exoskeleton almost immediately toggled back to the open position, causing the subject to drop the block.

While the subject was able to activate the extensor by attempting to contract her flexor, it is important to consider the implications of this control method. The question becomes, "Should we be training the patient to use an action that is not extended to recruit a specific muscle?" Will wrong practice result in false connections being established? These are valid research questions and they should be considered in the future of EMG research towards impaired device control.

6.3.3 Voice Control

Voice recognition is a largely growing tool being used in homes all over the country. Another application for voice recognition is device control; in (Ochoa et al., 2009) researchers used voice commands to operate a hand exoskeleton (Ochoa et al., 2009). Voice control was chosen as an alternative control mechanism for manual and EMG control. From the first session of Box and Blocks testing with the HOPE Hand 1.0, pseudo voice control was used, as described in Chapter 3. During this session, it was observed that voice recognition could have rehabilitative potential. The user had to plan their hand placement, decide if they wanted the hand exoskeleton to open or close, and then verbalize which command they intended while maintain positioning with the block. According to the physical therapist, coordination of these tasks is great therapy.

A simple version of voice control was implemented to test the concept that voice control is an intuitive user method. An EasyVR module for Arduino was used to recognize voice commands. The module comes pre-programmed with word sets commonly used for robotic applications such as "move", "turn", "hello", and "attack." The EasyVR Command program allows the user to train the module to recognize new commands. This feature was used to train the module to recognize when the subject said "open" and "close." Training new commands required the user to record themselves saying the word twice. While it is capable of training any voice command, the variability is limited because there is only a training set of two.

While the subject had no difficulty verbalizing "open" and "close" to train the EasyVR module, she struggled during testing because her intonation changed. It became apparent that even slight variations in intonation, volume, microphone distance caused the words to be unrecognizable by the EasyVR module. To rectify this problem in the immediate future, it would be ideal to modify and extend the training set to include more than two voice samples. Using voice control the subject was able to transfer one block in training and one block in testing (Table 6).

A future embodiment of voice control could be executed using a Android or Apple phone application with Google cloud speech-to-text API or Siri to recognize verbal commands. When the phone recognizes the verbal command a movement command would be sent to the hand exoskeleton over blue tooth connection.

6.4 Conclusions from Study

When the subject was asked which method she thought was the easiest to use, she said voice commands. When asked which method was the hardest to use, she said button because the foot pedal was hard to press physically, and when asked which one had a high potential for learning, she said EMG control. While all three of the methods were implemented, the subject struggled with each implementation. If these methods were developed and altered slightly, the results would show further improvement in a future study.

Even though the Box and Blocks test is used to evaluate manual dexterity, its goes beyond picking up blocks because the blocks gets locked together to produce a flat surface. A critical part of manual dexterity is being able to pick up the blocks despite being in this flat configuration. Therefore a modified version of the Box and Blocks test should be conducted to discover the true potential of the HOPE Hand 2.0 and the three user input methods. This modified test should resemble the test conducted in the first testing session with the HOPE Hand 1.0, where blocks were put on the table and the subject was asked to pick up the

blocks and put them in a box. This modification presents the blocks with five out of six surfaces exposed for the user to grab, while the formal Box and Blocks test presented a significant number of blocks with one-four sides exposed.

6.5 Summary of Contributions

The HOPE Hand 2.0 performed functional grasps repeatedly without modifications, indicating the redesign of the device was successful. The comfort of the device was improved as per the lack of irritation marks on the fingers, hand, and wrist.

Manual control, EMG control, and voice control were implemented with the HOPE Hand 2.0. The Box and Blocks testing results suggested that voice control would be a successful and intuitive way for some patients to control their hand exoskeleton with proper training and improved voice recognition implementation. I have implemented a simple hardware solution and suggested a possible solution, involving Google cloud speech-to-text API, which could be integrated with the hand exoskeleton system in the future.

7 Discussion and Future Work

This thesis work demanded knowledge of user study design, technical design skills, data processing techniques, and sensor integration. When trying to conduct a user study, it is important to use standardize tests but also be open to modifications which can better display the capabilities of the design. Throughout the redesign of the hand orthosis, a constant theme was trial and error. To come up with a successful design, you need to move on from your old ideas and iterate. Data processing of EMG signals is a field in and of itself, making it hard to grasp all of the concepts, but there is a lot of literature to guide the process. When concluding the viability of EMG control for impaired subjects, it was import to consider the implications of an accurate intention detection, using the wrong muscle. Overall this thesis explores a variety of well-studied topics, and topics that have yet to be thoroughly explored by the greater scientific community.

7.1 Conclusions

The original version of the HOPE Hand was tested on an impaired individual to evaluate the performance of the mechanics and identify areas to address in the redesign process. The HOPE Hand 2.0 was created after addressing all of the concerns from the first round of user testing. An EMG study was conducted to evaluate EMG as a viable option for device control for impaired users. Results suggest that approximately 55% of the impaired subjects included in the study would not be successful using an EMG controlled device. Manual control, EMG control, and voice control were implemented with the HOPE Hand 2.0 and the user study was repeated. The mechanics of the device performed reliably and comfortably, indicating the redesign successfully mitigated the identified problems. All three user input methods showed promising potential, which will be further realized in future testing.

This research aimed to contribute to a growing landscape of upper extremity assistive tools, with the goal of increasing the inclusivity of assistive devices to

improve the quality of life for a diverse group of impaired individuals.

7.2 Suggested Future Work

While this thesis work has concluded, the HOPE Hand should continue to be developed through user studies, exploration and improvement of user input methods, along with evaluating the possibilities of integrating new sensors. A huge challenge for creating wearable assistive devices is that people with impairments often find ways to compensate for their disability. Therefore, their compensation techniques might be easier for them instead of learning how to use a hand exoskeleton. The goal for assistive devices is to offer the user more function than they have using their compensation techniques. This should be kept in mind as the future work continues to develop the HOPE Hand.

7.2.1 Hand Exoskeleton Improvements

Force feedback is an improvement to be made to quantify the amount of assistance you are providing the user. By knowing how much force the device is applying, and the position of the finger, you can collect data on how much assistance the device is providing to the user.

Continued work on developing a customization technique for the hand exoskeleton would be beneficial. While the printed parts of the exoskeleton are a generic small, medium, or large size, the hand back plate would be more comfortable if it was more accurately fit to the user and if the knuckle placement was more customized.

Additional sensors to measurement motion, speed, and position could be incorporated into the hand exoskeleton design, as long as they don't drastically change the structure of the hand exoskeleton, significantly increase the weight, or add bulk. These sensors could be used in conjunction with the user input methods to provide a confidence level based on multimodal inferences from the sensor measurements. Essentially, the sensor measurements would be used to calculate

the probability of the occurring event to help to the exoskeleton decide if it is confident enough to change the state.

7.2.2 User Studies

The user study in Chapter 6 should be repeated with modifications to the Box and Blocks test and improvements to the user input methods. By placing the blocks on the table in front of the user, one at a time, the full potential of the device and the user input methods can be examined. This would also allow better comparisons to be made across the three user input methods, as it is difficult to draw conclusions when the results are so close in number, such as in Table 6.

Within the next few years, after further refining the HOPE Hand, a study should be conducted on the extended use of the HOPE Hand with 2-4 patients. HOPE Hands would be built and distributed to 2- 4 potential users who would incorporate the use of the device into their daily life. The trial would run 6 weeks total, with the subjects visiting their physical therapist every week to document any rehabilitative improvements. This would validate the concept of the design and act as a preliminary form of clinical trials. Extended user studies would allow us to get feedback on how useful the tool is day-to-day, as well as any rehabilitative effects of the device.

7.2.3 User Control Methods

While I am skeptical that current EMG technology is a universally effective user input method, I believe that with further research into sensor creation and algorithm development more opportunities to address the UMNS sub-population with unreliable, positive symptoms will become available.

Voice control is a promising user input method, as voice activated instruments have become a common part of daily life. Future work should be done on creating a phone application for voice recognition to operate the hand exoskeleton via Bluetooth using verbal commands.

Different combinations of user input methods would also be valuable. I think the most important qualities to consider when exploring new user input methods are reliability, the ability to integrate the control into their life (as in not affecting or preventing other activities), and, ideally, the user input method could be a vehicle for rehabilitation and retraining the damaged neural pathways.

8 Chapter 10. Other Biomedical Robotics Contributions

8.1 ARMI/Biofab USA Automated Coating Project

As a Research Assistant on a project titled "Automated coating of cell culture surfaces with growth factor releasing polyelectrolyte multilayers," I was tasked with creating a Bench-scale automated coating process and device as well as producing a components/equipment list for industrial scale automated process. The manual process for the microcarrier coating takes approximately four hours with fairly constant attention. My chemical engineering counterpart and I were able to refine the process by using syringes to infuse and decant the coating substances with the microcarriers.

I designed and built a bench-scale prototype for coating five times more microcarriers per batch. I also compiled a list of equipment that can be used in the next year to industrialize the process. A photograph of the prototype can be seen here. Servos are used to turn the valves on the manifold to allow liquid to be infused from the desired chemical. After the syringes draw the liquid up, the solution is agitated for 15 minutes. After 15 minutes, the chemical is pressed out of the syringe using the syringe pump, and sent back into the original receptacle that it came from. In between every chemical coating step there are two wash steps. Water is drawn into the syringes and then pressed out of the far end of the manifold into a waste receptacle.

While the subject of the project is not similar to my thesis work, bio fabrication automation is a very important area within biomedical robotics because it allows for these bio fabrication processes to be more consistent, efficient, and require less of a person's time. This project challenged me to learn about topics that I have never encountered, such as polyelectrolyte multilayers, substrate coating, and automation control technology.

8.2 Human Driver Motion Study

During a course project for Human and Robot Synergy, the team designed and conducted an IRB approved human driver motion study. In order to learn about motion primitives of driving, subjects were asked to use a driving simulation to complete a virtual road course. The experiment was broken down into five parts: task description, intake survey, practice session, data collection, and post-session survey. The idea was to collect data about how people operated the steering wheel and the pedals so we could extract motion patterns and learn the trajectories. These learned trajectories were turned into a motion primitive library. OpenSim was used to reproduce these motion primitives in simulation. The human driver model could then be integrated into the vehicle model, allowing us to observe the human-vehicle interactions (Mbanisi, Kimpara, Meier, Gennert, & Li, 2018). This project allowed me to apply my knowledge of human studies design to a topic which was new to me. Through this project I was introduced to Dynamic Motion/Movement Primitives as well as biomechanics modeling using OpenSim.

A Appendix

	Part	Y	X	Z	Dist	Thickness	Radius (O)	dius (I)	Offset	Proportion
	Tess									
Hand Back	MainPart	15	72.5			5	56.3	51.3		1
	MainPart (Main Length +z)			50						
	MainPart Cut		60	35			20			
	Inter-knuckle distance (Sketch 23)				22.5					
	Brace distal corner distance (driven)		*85*	*17.17*	*86.72*					
	Knuckle Piece (+x left)			40 (refe	17.5	10			1.7	0.02344
FingerSplintIndex	Width		0.83							
	Curved tip length			0.45						
	Fingertip radius						0.43			
	Hight to ridge	0.7 (0.6)								
	Part thickness				0.07					
	Finger thickness (inner)				0.63					
	Finger thickness (outer)				0.54					
FingerSplintThumb	thickness					0.65				
	width				0.9					
	lengthpipdip				1.75					
ProximalGuide	Arc height			2						
	Arc width		15							
	Length	20								
IndexMedial	Arc height			3						
	Arc width		18							
	Length	22.5								
Thumb Plate	ProfileSketch			34		5	25	20		
	Arc radius						20			0.27586
	Plate length	<-- Pl	40							
	Rey									
Hand Back	MainPart	16	75			5	55.78	50.78		
	MainPart (Main Length +z)			50						
	MainPart Cut		60	35			20			
	Inter-knuckle distance (Sketch 23)				25					
	Brace distal corner distance (driven)				*86.72*					
FingerSplintThumb	thickness					0.72				
	width				0.95					
	lengthpipdip				1.5					

Figure 55: SolidWorks parts measurements used to calculate/document measurement of hand geometry vs. measurements of CAD parts to ensure that the printed parts would fit (accomodation for tolerances,etc.)

	Imperial (inches)					Metric (mm)					
	Measured Test		Anthropometric					Anthropometric			
Measurement	**Rey**	**Tess**	**Men 50%ile**	**Women 50%ile**		**Rey**	**Tess**	**Men 50%ile**	**Women 50%ile**		
Hand length	7.0	6.6	7.5	6.9		177.8	167.64	190.5	175.3		
Hand breadth	3.3	3	3.5	2.9		83.8	76.2	88.9	73.7		
3rd finger length	4.4	3.9	4.5	4.0		111.8	99.06	114.3	101.6		0.2019
Dorsum length	2.8	2.7	3.0	2.9		71.1	68.58	76.2	73.7		
Thumb length	2.7	2.4	2.7	2.4		68.6	60.96	68.6	61.0		
Parts for GV:	Global Variables					Rey's CAD Dimensions:					
Hand Back Plate	Hand breadth		Dorsum length		mm	BaseHeight:	51.85	Hand breadth:	79.75		
Thumb Plate	Hand breadth		Thumb length		mm	ThumbRadiu	22.00	LoftLength:	45.00		
Thumb Splint	Hand breadth		Thumb length		in:	Width:	0.95	Thickness:	0.72	Length:	1.6875
Index Finger Splint	Hand breadth		Hand length		in:	Width:	0.84	Thickness:	0.66	Length:	1.8030
Proximal Guide	Hand breadth		3rd finger length		mm	Width:	16.50	Length:	23.97		
~~Index Medial~~	~~Hand breadth~~		~~3rd finger length~~								

						Index Finger (second crease to MCP)					
						0.229166666		0.25892857			
					Tess:	38.4175	*Rey:*	46.0375			
CAD (mm)			*Ratio*	*CAD (mm)*			*Ratio*	*CAD (mm)*			*Ratio*
Tess Reference Ratios (original CAD part)											
50	Base height to dorsum length		0.7291	72.50	Main width to hand breadth:		0.9514				
20	Thumb radius to hand breadth:		0.2625	40.00	Loft length to thumb length:		0.6562				
18.288	Thickness to hand breadth:		0.2400	24.13	Width to hand breadth:		0.3167	1.5	Lengthpipdip to thumb length:		0.6250
15.24	Thickness to hand breadth:		0.2000	19.30	Width to hand breadth:		0.2533	1.7	Lengthpipdip to hand length:		0.2576
15	Width to hand breadth:		0.1969	20	Length to prox. phalange		0.5206				

Figure 56: Anthropometric ratio table used to generate hand geometry measurements that were not included from the scan as ratios of the measured segments

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