Western University Scholarship@Western

Electronic Thesis and Dissertation Repository

8-23-2021 1:30 PM

Data and Sensor Fusion Using FMG, sEMG and IMU Sensors for Upper Limb Prosthesis Control

Jason S. Gharibo, The University of Western Ontario

Supervisor: Naish, Michael D., *The University of Western Ontario* A thesis submitted in partial fulfillment of the requirements for the Master of Engineering Science degree in Mechanical and Materials Engineering © Jason S. Gharibo 2021

Follow this and additional works at: https://ir.lib.uwo.ca/etd

Part of the Electrical and Electronics Commons, Electro-Mechanical Systems Commons, and the Signal Processing Commons

Recommended Citation

Gharibo, Jason S., "Data and Sensor Fusion Using FMG, sEMG and IMU Sensors for Upper Limb Prosthesis Control" (2021). *Electronic Thesis and Dissertation Repository*. 8100. https://ir.lib.uwo.ca/etd/8100

This Dissertation/Thesis is brought to you for free and open access by Scholarship@Western. It has been accepted for inclusion in Electronic Thesis and Dissertation Repository by an authorized administrator of Scholarship@Western. For more information, please contact wlswadmin@uwo.ca.

Data and Sensor Fusion Using FMG, sEMG and IMU Sensors for Upper Limb Prosthesis Control

Jason S. Gharibo

M.E.Sc. Thesis, 2021 School of Mechanical and Materials Engineering The University of Western Ontario

Abstract

Whether someone is born with a missing limb or an amputation occurs later in life, living with this disability can be extremely challenging. The robotic prosthetic devices available today are capable of giving users more functionality, but the methods available to control these prostheses restrict their use to simple actions, and are part of the reason why users often reject prosthetic technologies. Using multiple myography modalities has been a promising approach to address these control limitations; however, only two myography modalities have been rigorously tested so far, and while the results have shown improvements, they have not been robust enough for out-of-lab use. In this work, a novel multi-modal device that allows data to be collected from three myography modalities was created. Force myography (FMG), surface electromyography (sEMG), and inertial measurement unit (IMU) sensors were integrated into a wearable armband and used to collect signal data while subjects performed gestures important for the activities of daily living. An established machine learning algorithm was used to decipher the signals to predict the user's intent/gesture being held, which could be used to control a prosthetic device. Using all three modalities provided statistically-significant improvements over most other modality combinations, as it provided the most accurate and consistent classification results. This work provides justification for using three sensing modalities and future work is suggested to explore this modality combination to decipher more complex actions and tasks with more sophisticated pattern recognition algorithms.

Index terms— Human–machine–interface, sensor fusion, data fusion, upper limb prosthetics, gesture recognition, machine learning.

Lay Summary

Living with a lost limb can be extremely challenging as the activities of daily living become more difficult. Robotic prosthetic devices have been developed to help amputees with these activities to improve their quality of life. The available robotic prosthetic devices are capable of giving the user more functionality, but the methods available to control these prostheses restrict their use to simple actions. Furthermore, the limitations of the available controls usually lead to rejection of the prostheses that they are attached to because they are unreliable and lead to user frustration. Thus, it is very important to develop a method of prosthesis control that is reliable, simple, and intuitive to use.

The goal of this project is to create a system that can provide natural, reliable and intuitive control of modern prosthetics for at-the-forearm amputees. This research aims to improve the ability of a prosthetic arm to distinguish between several complex gestures for improved control.

For this work, a device that detects muscle information from electrical activity, physical changes, and motion changes of the arm was designed. The device allows for muscle information to be collected from the three sensor types while a participant performs hand/wrist gestures in arm positions important for activities of daily living. After the data was collected, it was analyzed using pattern recognition methods determine whether using three sensors is beneficial for finding patterns in the data associated with muscle activity.

Acknowledgements

First and foremost I would like to thank my loving family for supporting and being patient with me while I finish my almost 9th year of post-secondary education.

I would like to thank my supervisor Dr. Michael Naish for finding an interesting problem to solve, and supporting the project in its up and downs. From my colleagues I would like to thank Marco Gallone for his sheer knowledge and tutoring prowess, and George Bousygine and Tehreem Hassan for their electrical and electronics knowledge which helped to design the custom arm band used for this work. I would also like to than Mena Kamel for always setting a high bar for focus and hard work to strive for, and Jacob Tryon and Memo Collí-Alfaro for sharing their experiences working with EMG so that the learning curve was not as steep for me. Lastly I would like to thank Dr. Yue Zhou and and Dr. Brandon Edmonds for helping to guide me on the overall graduate school process.

Contents

\mathbf{A}	Abstract i									
Lε	Lay Summary ii									
A	cknov	wledgements	iii							
Τa	able (of Contents	iv							
Li	st of	'Figures v	iii							
Li	st of	Tables	x							
N	omer	nclature and Acronyms	xi							
1	Intr	roduction	1							
	1.1	Motivation	1							
	1.2	General Research Problem	2							
	1.3	Objectives and Hypothesis	3							
	1.4	Scope	5							
	1.5	Overview of the Thesis	6							
2	Lite	erature Review	7							
	2.1	Human Hand Anatomy and Kinetics	7							
		2.1.1 Nervous System	7							
		2.1.2 Muscular System	8							

		2.1.3	Kinetics and Activities Important for Daily Living	10
		2.1.4	Amputee Physiology	11
		2.1.5	Conclusion	12
	2.2	Prosth	esis Technology	13
	2.3	Non-Ir	avasive Myocontrol Sensors	14
		2.3.1	Surface Electromyography	15
		2.3.2	Force Myography	19
		2.3.3	Inertial Measurement Unit	22
	2.4	Multi-	modal Myography	23
		2.4.1	sEMG+FMG	24
		2.4.2	sEMG+IMU	25
		2.4.3	FMG+IMU	26
		2.4.4	FMG+EMG+IMU	26
		2.4.5	Conclusion	27
	2.5	Data S	Set Creation	27
		2.5.1	Signal Acquisition	28
		2.5.2	Signal Filtering	29
		2.5.3	Signal Segmentation	30
		2.5.4	Feature Extraction	30
	2.6	Patter	n Recognition Methods	33
		2.6.1	Artificial Neural Networks	33
		2.6.2	Support Vector Machines	34
		2.6.3	Linear Discriminant Analysis	35
		2.6.4	Regression	36
	2.7	Conclu	usion	36
3	Dat	a Colle	ection	38
	3.1	Equip	nent	39
		3.1.1	FMG Design Considerations	40

		3.1.2 sEMG Design Considerations	41
		3.1.3 Multi-modal Integration	43
	3.2	Signal Acquisition	46
		3.2.1 Participant Recruitment	46
		3.2.2 Experimental Protocol	46
		3.2.3 Multi-modal Device Placement	47
		3.2.4 Data Collection Procedure	48
4	Dat	a Processing and Pattern Recognition	51
	4.1	Signal Filtering	52
	4.2	Signal Segmentation	55
	4.3	Feature Extraction	56
		4.3.1 Standardization	58
	4.4	Data Set Creation	59
	4.5	Pattern Recognition	60
5	Res	ults and Discussion	62
	5.1	Overall Accuracy Results	63
	5.2	Arm Position Accuracy	66
	5.3	Classifier Performance	68
	5.4	Conclusion	70
6	Cor	cluding Remarks	72
	6.1	Contributions	72
	6.2	Future Work	74
R	efere	nces	78
A	ppen	dices	87
\mathbf{A}	Per	missions and Approvals	87
	A.1	Ethics Approval	88

Curriculum Vitae

vii

List of Figures

2.1	Anterior and posterior views of the muscles in the forearm	9
3.1	Complete multi-modal arm band with exposed IMU board	39
3.2	A commercially-available Interlink 402 FSR with and without modifications	40
3.3	Integrated FMG, sEMG and IMU PCB	43
3.4	Assembled multi-modal arm band board	43
3.5	Exploded CAD view of the multi-modal arm band module	44
3.6	Block diagram of the FMG, EMG, and IMU data collection hardware $\ \ldots \ \ldots$.	45
3.7	Complete multi-modal arm band system	45
3.8	Multi-modal arm band affixed to participant's forearm	47
3.9	Data collection GUI	49
3.10	Hand/wrist gestures that were recorded	50
3.11	Arm positions that were recorded	50
4.1	Plotted raw FMG data	53
4.2	Plotted IMU showing the effect of arm position changes	54
4.3	Plotted raw EMG data	56
4.4	Window segmentation visualization	57
4.5	Summary of the data set creation process	58
4.6	Visualization of how the modality combination data sets were organized \ldots .	59
5.1	Classification accuracy of each modality combination	65
5.2	Classification accuracy of each modality combination for each arm position \ldots .	67

5.3	Confusion matrices for each modality combination		69
-----	--	--	----

List of Tables

3.1	Summary of	participant	information																		•		46	;
-----	------------	-------------	-------------	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	---	--	----	---

Nomenclature and Acronyms

Latin Letters

p	Order of the autoregressive model
w_i	White noise error term
X	Feature value
Z	Normalized value

Greek Letters

η_p^2	Proportion of variance attributed to an independent variable
μ	Sample mean
σ	Standard deviation of the sample set

Acronyms

ADC	Analog-to-digital Converter
ADL	Activities of Daily Living
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
API	Application Programming Interface
AR	Autoregressive Coefficients

NOMENCLATURE AND ACRONYMS

CAD	Computer Aided Design
DAQ	Data Acquisition
DOF	Degrees of Freedom
EMG	Electromyography
FMG	Force Myography
FSR	Force Sensing Resistor
GUI	Graphical User Interface
HMI	Human-machine-interface
IMU	Inertia Measurement Unit
LDA	Linear Discriminant Analysis
MAV	Mean Absolute Value
MAVs	Mean Absolute Value Slope
ML	Machine Learning
MUAP	Motor Unit Action Potential
NI	National Instruments
PC	Personal Computer
PCB	Printed Circuit Board
RPTF	Resistive Polymer Thick Film
sEMG	Surface Electromyography
SVM	Support Vector Machine
SVR	Support Vector Regression
TMG	Tactile Myography
WL	Waveform Length
ZC	Zero Crossings

Chapter 1

Introduction

1.1 Motivation

Whether someone is born with a missing limb or an amputation occurs later in life, living with a missing limb can be extremely challenging. One's ability to conduct simple activities that are important for daily living are limited and can hinder a person's ability to live independently [1]. To address this concern, highly functional prostheses have been extensively researched and developed. These devices have the potential to give those with missing full or partial limbs functionality close to that of their missing biological counterparts. With added functionality, these prosthetic devices introduce more complexity to the already difficult challenge of being able to control them. Thus, the biggest limitation in this field has become the user's ability to control their prostheses [2–4].

Users often reject prosthetic technologies (rejection rates are as high as 75% [5]) because traditional prosthetics have limited usefulness, and the high-tech, newer ones have frustrating, nonintuitive controls that are unreliable [6]. To address this concern, a system that intuitively and accurately detects a user's movement intent must be created. This can bring users a natural feeling way to control their prosthetic devices. The success of this system can bring the field closer to a solution and generally speaking, advance the fields of sensor fusion and human-machine-interfaces for the control of mechatronic systems.

1.2 General Research Problem

Pairs of electromyography (EMG) sensors were commonly used to provide those with missing limbs a natural feeling human-machine-interface (HMI) for controlling prosthetics. With the advancement of mechatronic systems, these prostheses have become very complex, and the requirements for communication between prosthesis and user more demanding—far beyond what a few EMG electrodes are capable of. Extensive work has been done to make EMG more effective using various sensing techniques, sensor arrays and pattern interpreting methods; however the systems remain limited [3, 7]. Force myography (FMG) is a more recent development and is capable of discerning between multiple grasps, but is still limited in its robustness and accuracy [8, 9]. A potential solution is to fuse multiple sensing modalities so that, where each individual modality is limited, they may compensate for one another. Ultimately, this would give the pattern interpreting algorithm more reliable information to work with. To this effect, inertial measurement unit (IMU) sensors have been paired with EMG or FMG in order to record spatial information—giving the pattern recognition algorithm more distinct cases to decipher [10–12]. This method has been found to increase the robustness of the system, possibly accounting for some of the sensor limitations that can be problematic for EMG and FMG [4, 13]. Recent studies have also tried fusing EMG and FMG, and have accounted for an incremental increase in accuracy [14, 15]. Multi-modal myography is being affirmed as one of the main ways forward in this field.

This work proposes that by integrating EMG, FMG and IMU sensors into a single system, it is possible to more accurately and consistently decipher between multiple grasps and arm positions that are important for the activities of daily living. Overcoming this hurdle can unlock the functional potential of modern prostheses.

1.3 Objectives and Hypothesis

The goal of this thesis is to create a robust, accurate and intuitive HMI that detects hand motion intent for transradial (at the forearm) amputees in order to provide a natural, reliable, and comfortable way to control modern prostheses. To help drive this field closer to a solution, this thesis will focus on determining whether simultaneously using three sensing modalities helps to increase the classification accuracy of gestures that are important for activities of daily living.

The forearm contains all of the muscles that act to control the hand and wrist. From these muscles, a significant amount of information can be obtained and used to infer intent. The field of myography uses various methods/sensors to detect muscle activity and can be used to distinguish between complex gestures using pattern recognition algorithms. A myography device placed on the forearm can detect information about what the user intends to do with their wrist and hand. Surface electromyography (sEMG) and FMG sensors have been extensively tested for this purpose.

Recorded data from myography sensor modalities can be sent to a pattern interpreting algorithm to decode the user's intent. Machine learning methods have been used successfully for this application and have become the standard way to associate myography signal patterns with a user's intended gesture or movement pattern [3, 7, 14]. The deciphered signal information can be easily used to control prostheses and can ultimately provide the user with a natural feeling way to control their advanced robotic prosthesis for day-to-day use [2]. Although the concept of using machine learning to decipher gestures from myography sensor data has been validated, there has been limited success outside of the lab. A large part of this can be attributed to sensor limitations. For example, the consistency of sEMG signals is limited by moisture level changes on the skin [16]. To combat this challenge and discover a more robust method of control, using multiple myography types at once is being explored. Systems that use two sensing modalities often achieve greater accuracies than using just one sensing modality and it has been unanimously stated that using multiple sensing modality types is one of the main ways of getting these systems to perform adequately [4, 14, 16]. The theory behind this potential solution is that the interpreting algorithm (machine learning model) gets both supplemental information (if a sensor's information is insufficient), and redundant information (to confirm patterns in the signal) from the combination of sensors [7]. Still, the systems explored to date have their limitations and have not been able to provide adequate robustness and accuracy.

For this work, a device that combines sEMG, FMG, and inertial measurement sensors was designed. The device allows for data to be simultaneously collected from the three sensing modalities while a user performs hand/wrist gestures in arm positions that are critical for activities of daily living (i.e., pinch, grasp). A well-established machine learning (ML) algorithm called a support vector machine (SVM) is used to decipher the signal information. The use of an already validated ML algorithm was chosen to limit the number of variables under consideration and focus the research on testing the efficacy of using these three sensor modalities simultaneously—something that has only been tested once before in a preliminary study that achieved up to 90% accuracy with just a simple control strategy and without the use of ML. There were only 10 subjects in this study and no statistical analysis was conducted to investigate significance of the results [17]. For this thesis, obtained classification accuracies from the device using just two sensors (EMG and FMG, EMG and IMU, FMG and IMU) will be compared against classification accuracies obtained using all three sensors in an extensive study to draw clear statistical conclusions.

This research will be used to test the hypothesis of whether simultaneously using these three sensing modalities provides an increase in gesture classification accuracy. It is expected that the machine learning and multi-modal myography sensing system will more consistently detect an amputee's intended gestures, and give users a classification accuracy of above 90%, above which usability becomes adequate, and a prosthesis becomes practical to use [18]. This work will be able to provide justification for future work: whether using these sensing modalities provides an increase in accuracy, and whether using the multi-modal system should be explored further in conjunction with advancements in other avenues such as signal processing and pattern recognition methods.

1.4 Scope

The purpose of this thesis is to delve further into the potential benefits of sensor and data fusion for intuitive prostheses control. For the first time, three different myocontrol, co-located modality types will be simultaneously recorded and used for ML pattern recognition, and the results rigorously assessed. A device that integrates EMG, FMG and IMU sensors into a single band was created for this work and used to collect data from a subject's forearm while they performed seven hand gestures in three different arm positions. The gestures were chosen for their importance as activities of daily living, and as a benchmark for assessing the accuracy and robustness of the system when classifying gestures. The data from the sensors was processed using well established pre-processing and pattern recognition methods. An optimized support vector machine was chosen as the pattern recognition model as it is widely accepted for this purpose. It is also the precursor to the similarly formulated support vector regression model that is used for the logical next step, and more challenging task of simultaneous and proportional control [8]. The less complex, precursor model was chosen to focus this work on sensor and data fusion, and to validate the new multisensor hardware. Various data and sensor fusion configurations were tested, and the model's ability to accurately classify gestures was assessed. This work lays the groundwork for advanced uses of this device, such as proportional control and task-oriented experiments. The results of this experiment are presented and discussed.

1.5 Overview of the Thesis

The structure of this thesis is summarized in the outline below:

- Introduction: Presents the motivation, hypothesis, objectives, and scope of Chapter 1 this work. Chapter 2 Literature Review: In depth background and state-of-the-art information on the forearm and hand anatomy, robotic hand prostheses, non-invasive sensing methods, and pattern recognition algorithms for controlling advanced prostheses. Chapter 3 Data Collection: A thorough description of the equipment designed and built for the purpose of sensor fusion for prosthesis control, allowing for the collection of EMG, FMG, and IMU data simultaneously. This chapter includes the experimental protocol that was used to acquire data points. Chapter 4 Data Processing and Pattern Recognition: Outlines the methods that were used for signal segmentation, feature extraction, and creating data sets for subsequent pattern recognition. Then specifies the pattern recognition algorithm and model training methods that were used. Chapter 5 Results and Discussion: Presents and discusses results of the multi-modal device's accuracy compared to other state-of-the-art systems. Chapter 6 Concluding Remarks: Highlights the contributions and limitations of this work and provides recommendations for future work.
- **Appendix A** Permissions and Approvals: Includes ethics approval form.

Chapter 2

Literature Review

2.1 Human Hand Anatomy and Kinetics

The human body is an extremely intricate and intertwined biological system. To extract information from this system using sensing modalities, it is important to understand how the underlying system works. For practical use of this knowledge, it is also important to know what movements are critical for human life. For example, to understand the kinematics and biological phenomena of grabbing and drinking from a cup, it is important to understand the anatomy of the forearm and how the body instructs itself and moves through space. The insights learned in this section will be used to determine what phenomena are occurring, what may be measurable and in what scenarios the gesture recognition system will need to work. This section of the review will focus on the most important factors affecting people with missing partial limbs at the elbow and below.

2.1.1 Nervous System

The biological network that transmits information to and from parts of the body is comprised of individual units called nerve cells, otherwise known as neurons. Neurons are either of the sensory or motor type and function as their names imply. The cause of motor neurons' signals is either from reflex actions or from conscious thought/the somatic system. These are otherwise known as involuntary versus voluntary actions. The signal effects caused by these actions are not easy to isolate as they often put motor neuron branches or pathways into effect [19]. Neurons communicate via the nervous system through signals that are measurable and detectable as electrical potentials on the surface of the skin [20]. The electrical potentials arise from chemical changes within the system and travel as impulse "waves of negativity" that move close to the speed of sound [19].

The nervous system innervates the muscles of the body and communicates to them at an interface called the neuromuscular junction. Neurons at the neuromuscular junction instruct muscles to contract and the signals spread into adjacent muscle cells. As the electrically detectable signal sweeps through a muscle membrane it sparks internal events that cause the muscle to contract [21].

The nerve supply to the upper limb originates at the spinal column, then branches through a hub of nerves called the brachial plexus [19]. From the brachial plexus, the main nerves that control the hand, wrist and forearm can be found. They are the median, ulnar and radial nerves. The median nerve runs deep on the anterior forearm and controls most of the flexors of the forearm as well as the thumb, index and middle finger. The ulnar nerve wraps around the funny bone and passes along the lateral side of the forearm, supplying most of the hand muscles, as well as flexion of the ring and pinky finger. The radial nerve runs on the posterior side of the forearm and is mostly for sensory nerves, but also has motor nerves to control extension of the fingers [21].

2.1.2 Muscular System

When the nervous system signals for a muscle to activate, it initiates internal events in the muscle that cause it to contract [21]. These internal events are also detectable as electrical potentials that correspond to the number of motor units activated and are a function of the musculature demand. When the muscle is relaxed, it generates very little electrical potential [3]. Contracting/relaxing muscles, and their attachment to the skeletal system via tendons, are the means by which the human body moves [21]. When muscle fibres are contracted, they bring the ends of the muscle together and pull the attached skeleton to move it through space. When the tension is released, the skeleton is freed to move in the opposing direction. Contraction causes muscles to shorten and is visible as a volumetric change [22]. This is easily observed when, for example, one flexes their bicep to bring their forearm to their shoulder, and the bicep muscle becomes more prominent near



Figure 2.1: Anterior and posterior views of the muscles of the hand, wrist and forearms. Reprinted, with permission [26].

the middle of the upper arm.

The main purpose of the muscular system is to perform various movements, which mostly consist of the activities important for daily living. These activities include tasks such as grabbing utensils or a cup to drink from, and using a key to lock and unlock a door [15]. The human hand/wrist is critical for these activities of daily living (ADL). In mechanical terms, the wrist is a three degree-of-freedom (DOF) system, making it extremely complex but also capable of these movements and more [23]. The human hand, capable of over forty-eight grasps and gestures, also adds considerable complexity and capability to the upper limb [24]. The degrees of freedom for the hand/wrist present themselves as flexion/extension, rotation (pronation/supination), adduction and abduction, as well as the movements of the digits [25].

All of the muscles used to control the hand/wrist pass through the forearm and are especially

prevalent at the part of the forearm with the greatest girth, as indicated by the red line in Figure 2.1. This spot is typically one-third of the distance from the elbow to the wrist and is usually the location chosen for sensing physical and electrical changes associated with interpreting a user's intended hand/wrist gestures [4, 8, 9]. Logically, it makes sense that relevant biological signals are detectable here since most of the signals and muscles used to control the distal limb pass through this area of the forearm.

Particular actions often emerge as branches of signals and chains of muscle activations. Dayto-day scenarios and the activities of daily living add to the complexity of these chains as there are several reflexive muscle paths that activate as functions of arm position, whether the limb is accelerating/decelerating, or whether the person is carrying something [22]. Between people, there are also differences in anatomical structure and movement idiosyncrasies. Even with a similar anatomical configuration, differences in limb size, skin thickness and muscle density are important to note [8]. Thus, although there are underlying muscle groups and phenomena that are similar among all humans, the signals are not deciphered easily; this is especially true outside of a lab setting.

2.1.3 Kinetics and Activities Important for Daily Living

The human hand, wrist and forearm are made up of twenty-nine bones with an intermingling relationship between muscles and nerves that make it capable of moving through a multitude of actions [27, 28]. In general, the human body allows people to perform intricate tasks and adopt different poses depending on the situation. Though complex, the capabilities offered by these systems are critical. Critical tasks are referred to as the ADL and were summarized by Peerdman et al. [29] as using zippers, making a bed, grabbing a cup and using utensils. These functional tasks all involve a grasping type, movement pattern and the subsequent release of an object [30]. Broken down into simpler motions, these activities are made up of sequences or combinations of pronation/supination of the forearm, flexion/extension of the wrist and the tripod, power grasp and open hand actions [11, 29, 31]. The importance of these particular actions is demonstrated by their repeated use in testing for transradial prosthesis and rehabilitation research [4, 11, 20, 24].

Depending on the action a person is trying to achieve, the body has several mechanisms that

help it adapt in the real/dynamic world. When the body is accelerating/decelerating, overcoming a force, moving in a particular orientation, or trying to stay balanced, the body activates muscles that are not necessarily associated with the intended action [30]. These phenomena are a form of the reflex actions discussed in Section 2.1.2. The residual, but necessary, reflexive muscle activations make it harder to distinguish the muscle patterns for particular gestures. In addition, physical injury or someone's physiological makeup can further cause variations in muscle activation patterns, making it even more difficult to associate muscle activation patterns to actions [19]. Although they are not simple to detect, there are still underlying patterns and behaviours that are repeated across the greater population [11].

2.1.4 Amputee Physiology

Although transradial amputees and those with intact upper limbs have similar physiology, there are anatomical and physiological differences that are critical to understand and consider. A defining feature of transradial amputees is that they are missing parts of their forearm, including their hand/wrist, and the functionality that the appendage provides. Partial limbs may be the result of trauma, disease, musculoskeletal tumours or the result of a procedure used to straighten a deformed limb. Some are also born with missing body parts [32, 33]. Whether the partial limb is missing as a result of trauma, surgery or childbirth, residual muscles that normally move the hand and articulate the wrist are often still there [6, 32]. Thus, the physiological principles discussed previously are still relevant; however, there are several additional challenges when working with individuals with fully- or partially-amputated limbs.

One of the challenges when working with amputee physiology is the variability of how the limb was lost. Even within the limited scope of transradial amputees, there are significant differences in amputation location along the forearm, and amounts of scar tissue, residual muscle and nerve damage [32, 34]. Campbell et al. [35] found that residual limb size was an important factor when determining how well underlying physiological phenomena could be detected. Another consequence of severing nerve and muscle is that the neuromuscular system begins autonomously looking for nearby sources of input or musculature to assist with movement. This biological process is not consistent and creates even more variability among amputees [34, 36]. Fortunately, with advances in amputation surgery, nerves, muscles and the residual limb can be preserved and manipulated to retain some similarity and optimality for prostheses control [37]. Still, the variability among transradial amputees can be substantial as the events that caused the amputation can be so different.

Another challenge for those with missing full or partial limbs is the lack of feedback past the point of amputation. Although it is possible for an ampute to control the physiology normally used to move the missing hand and wrist, the lack of an appendage makes it difficult for the amputee because of the lack of visual feedback, limited sensation and proprioception that make fine control nearly impossible [15, 38]. With limited proprioception, sensation, and visual feedback, it is mentally taxing for an ampute to specifically activate the muscles associated with particular movement patterns [12, 39]. This is important because researchers have been trying to use physiological signals proximal to the hand/wrist to predict what a person is intending to do with their appendage. Intent prediction based on measurable physiological phenomena is useful because it can provide amputees with a control mechanism for prostheses that is natural feeling and intuitive [4]. With the physiological limitations associated with a missing full or partial limb, it is not surprising that amputees consistently perform worse than able-bodied participants in experiments that use these signals to predict hand/wrist gesture intent [18]. Of note is that the relative performance between able-bodied and disabled subjects often remains the same, so performance can still be evaluated with able-bodied subjects, but one should assume that the system will perform worse on amputees [40].

2.1.5 Conclusion

This review of human anatomy and kinematics gave a foundation of the knowledge needed to understand of the relevant physiological phenomena that are important for transradial amputees and controlling prostheses. To have a natural-feeling prosthesis control method, it is critical that there are detectable physiological phenomena that can be deciphered and mapped to movement patterns for predicting motion intent [29]. Important, measurable phenomena of the upper limb are the volumetric changes and electrical potentials associated with muscle contraction [4]. Measuring these phenomena can give insights into what a person is intending to do with their hand/wrist. Orientation and momentum of the upper limb are also important factors for distinguishing between particular patterns. For hand/wrist control, these signals are best detected at the part of the forearm with the greatest girth [24]. Although it is well understood where and how these phenomena can be measured, the signals come from complex, intertwined systems that can be very challenging to decipher [11]. The task is made even more difficult with the physiological differences associated with having partial limbs. Fortunately, with partial limbs, there are still muscle groups and patterns associated with movements that make it possible to decipher, albeit more challenging to do so [40]. The techniques used to decipher these phenomena must overcome variability between subjects, such as skin thickness, scar tissue, gait, muscle definition and amounts of residual physiology [32, 34]. To restore lost functionality to a transradial amputee, the most important actions that they should be able to control (and that are often benchmarked) are pronation/supination of the forearm, flexion/extension of the wrist, and the tripod, power grasp and open hand actions [29].

2.2 Prosthesis Technology

A major goal of the prosthetics research community is to provide amputees with a prosthesis system that can be controlled as though it is an extension of the biological body [4]. Doctors often recommend prostheses to amputees, especially if the amputation occurs later in life, as the person is accustomed to the functionality of the missing limb [32]. The purposes of this recommendation are to avoid gait changes resulting from the loss of mass (to maintain balance), avoid unwanted attention to the amputee (for aesthetic purposes), and to restore the ability to perform at least some of the activities of daily living (provide functionality) [6, 33].

Today, amputees have several prosthesis types to choose from. All of the currently available prostheses fall into either the passive, body-powered, externally-powered or hybrid categories. Passive prostheses are primarily cosmetic but can be used to stabilize the body and the residual limb. Body-powered prostheses use forces generated by the residual limb or other body movements to control the prosthesis. A major advantage of body-powered systems is that the user can maintain fine and smooth control, but at the expense that the user is limited to very simple motions. Externally-powered prostheses use batteries and actuators for movement, and often use sensors on the residual limb as the inputs for control. Hybrid prostheses are a combination of bodypowered and externally-powered systems [32]. Most state-of-the-art research today focuses on the use of externally-powered systems. This is likely because they have the greatest potential to restore close-to-full functionality to the user. Some examples of commercially available, externallypowered prostheses are the i-Limb by Össur [41] and Be-Bionic by Ottobock [42], which already have the capabilities of mimicking the human hand and wrist.

Robotic appendages, which at this point are well developed, are only one part of the prostheticlimb-system. What remains is the extremely difficult component of the system that gives the amputee control of their prosthesis [2, 4]. This part of the prosthesis system is known as the control system [43]. Giving amputees control of multiple degrees of freedom — a fundamental feature of modern prosthesis systems — introduces incredible amounts of complexity for control [4, 44]. One approach alluded to previously uses sensors to extract signals from the body. Body signals must be recorded, processed and decoded for the robotic appendage to know how to behave for the user [43]. This is not an easy feat, and the challenges presented by these requirements makes the reliability of the prosthesis control system a major limiting factor — along with their cost and universality. Control system limitations contribute to why only 50–60% of amputees use a prosthetic limb, and why the newer technologies have a rejection rate as high as 40% [44]. Creating a sufficiently accurate, reliable, quick, universal and affordable control system is critical for the future of advanced robotic prosthesis use.

2.3 Non-Invasive Myocontrol Sensors

Myography is the field of measuring biological signals — typically muscular signals from the human body. These measurement signals are taken with myography sensors, which are either of the invasive or non-invasive type. Invasive myography sensors require surgery as they innervate the neuromuscular system directly, while, non-invasive myography sensors sit on the surface of the skin, making them more universal and often more economical [33]. Using non-invasive myography sensors with modern, externally-powered prosthetic systems has the potential to give amputees a simple, economical and natural feeling way to restore lost functionality.

To control a prosthesis as if it were a natural limb, the system must be able to interpret the gestural intent of the user [45]. Intent interpretation is the ability to infer user desires from available information. For a robotic appendage/control system, the available information is in the form of signal data from the sensor types chosen to measure relevant phenomena from the user. The success of a natural-feeling control system greatly depends on the sensors' ability to accurately and reliably detect relevant myographic phenomena of movement and important gestures [43]. For a natural-feeling, gestural-intent prosthesis control system to become widely adopted, it needs to interpret the users intent accurately and consistently in different arm positions. Also, the time delay between muscle contraction and prosthesis reaction must be under 300 ms [40, 46]. Meeting these criteria will ensure that real-time control is intuitive and practical to use [47].

Section 2.1 referred to many different biological phenomena exhibited by the human body while performing gestures important for the activities of daily living (ADL). The phenomena focused on were neuromuscular changes that could be detected as electric potentials on the surface of the skin, volumetric changes of the muscle, which are also detectable at surface level of the skin, and motion/orientation effects associated with movements. These phenomena can be detected by sEMG sensors, FMG sensors and IMUs respectively. Being able to detect and measure these phenomena gives the prostheses' control system information that can be relevant to particular movements and gestures [43].

2.3.1 Surface Electromyography

In 1948, EMG became the first myography modality used to drive a hand prosthesis [48]. EMG was pursued for prostheses control because of its ability to detect the electrical phenomena associated with muscle contraction, measured as a motor unit action potential (MUAP). This method allowed users to control their prostheses with their nervous system, which could give the user control of their prostheses as if it were a natural extension of their body. This technology was also successful because of its applicability to real-time control, since the onset of a MUAP can be detected approximately 100 ms ahead of any physical movement [31, 49].

Since EMG has been around for so long and has proven that it can be useful for prosthesis

control, it is the most thoroughly researched modality [50]. For most of time that EMG has been used for prosthesis control, it has been used for 1 degree-of-freedom (DOF) control, but with recent advancements in ML and pattern recognition research, it has also been found that more complex patterns can be discerned from the body using multiple EMG electrodes [31, 49]. As mentioned in Section 2.1, there are muscle patterns that activate that are associated with particular gestures. By using several EMG electrodes on these muscles, and using pattern recognition algorithms, these muscle activation patterns can be matched to movements and gestures that can be communicated to a prosthesis, giving the user seamless control of multiple DOFs and complicated gestures [51, 52].

There are two main types of EMG electrodes, which are surface EMG electrodes and intramuscular EMG electrodes. sEMG is preferable and more often used for prosthesis control than intramuscular EMG because it is able to detect MUAPs via electrodes on the surface of the skin versus intramuscular EMG, which must be inserted with a needle. Being non-invasive in this way also makes sEMG a cheaper and more comfortable solution that does not require surgery [51]. Since sEMG detects muscle activations from the surface of the skin, it detects activity from muscles that are not directly beneath the probing electrode, which has been found to be both beneficial and detrimental [52]. This phenomenon of detecting adjacent muscle activation is referred to as cross-talk. The detrimental effects have been mostly mitigated with advancements in signal processing, and the more important considerations have been deemed to be clinical considerations such as ease-of-use and cost, which are addressed by using sEMG [53].

sEMG electrodes can detect muscle activity from the skin using either wet or dry electrodes [54]. Wet electrodes are held in place by an adhesive substance and typically have better conduction with the skin and underlying MUAP. Unfortunately, they are impractical to use since they are often disposable, making them a recurring cost and wasteful. Wet electrodes are also less comfortable because they do not allow for airflow near the electrode. Reusable dry electrodes are the most practical since they do not need to be replaced and allow for airflow, but they are affected by limitations such as contact concerns with the skin, and electrode shift because they are only held in place with arm bands or pressure fit into sockets, and can cause artifacts in the signal [52]. Other hardware considerations such as electrode geometry, material, configuration and size are important factors that need to be considered when creating a successful system. Commercial sEMG systems

tend to use dome electrodes made of either stainless steel or titanium [42, 55]. The configuration of sEMG systems employed is monopolar, bipolar or high definition arrays, but bipolar configurations are by far the most used, and have had the most success in industry for this application [56].

The amplitude of an sEMG signal without amplification ranges from microvolts to low millivolt (0–6 mV peak-to-peak or 0–1.5 mV RMS) range [52]. Within this relatively weak signal is a considerable amount of information related to muscle activation and fatigue [46, 57]. The amplitude and frequency of EMG signals is also influenced by physiology, including fat, scar tissue, missing physiology, fatigue and sweat [52, 58, 59]. Sweat in particular is an important consideration, as the salinity of sweat helps conduct signals from the surface of the skin. Using dry electrodes is often limited because of a lack of good adhesion to the to the skin, but after some time with a sensor on the skin, sweat develops, which increases conductivity at the electrode. This phenomena is why signal noise from EMG tends to be high shortly after putting electrodes on the skin, versus after some time has passed. After sweat develops on the skin, the signal level increases and level of noise decreases [13].

For an sEMG system to be useful for advanced prosthesis control, the system needs to detect patterns of muscle activation. To do this, sEMG sensors should be placed on the muscles responsible for the movements to be deciphered [15]. Some researchers have tried targeting specific muscles, but this is not practical for an amputee to do every time they want to put on their prosthesis. One strategy is to use multiple sensors, or arrays of sensors in an area of interest, to increase the chance of landing on important muscles. An extreme example of this is highdefinition sEMG electrode arrays, which have been able to successfully classify hand gestures, but are expensive and computationally-demanding, making them unrealistic for affordable, real-time prosthesis control [60]. Having several electrodes does have its benefits, such as making it more likely for the sensors to be in a good location, and providing the pattern recognition algorithms ample information to decipher. A balance must be found between a sufficient number of sEMG sensors to measure adequate muscle activity information, but not make the system too financially and computationally-expensive.

To strengthen the possibility of good sensor placement while keeping the number of sensors down, groups have found general locations that have been successful at detecting the relevant signals for specific motions [4, 11, 15, 29]. For hand and wrist control, most groups put sensors one-third of the distance distal from the elbow (olecranon process) to the wrist (ulnar styloid process) [4, 20]. This is the same band of the forearm highlighted in Section 2.1 and Figure 2.1. Fortunately, these ideal EMG zones for hand and wrist control are often intact for transradial amputees [35].

The main benefits of sEMG are that it is the most extensively researched modality and that it is still being actively researched and used today. It is the only myography sensor used for commercial prosthesis control, which can be attributed to its robustness to arm position changes, and limited need to be precisely locate muscles, which are important factors for out-of-lab scenarios [55, 61, 62]. Specific to its use as a sensing modality for prostheses control, sEMG sensors are low power, can have a small form factor and have rapid MUAP detection, being able to detect actions even before the muscle makes physical changes [15, 18].

Although using sEMG for prosthesis control has been researched and been around the longest, researchers are still trying to find better modalities to use as sEMG on its own is not sufficiently capable [4]. The sEMG signal is complex and noisy, and in order to get relevant information, extensive, potentially expensive signal processing has to be done to it. Electrodes can experience noise due to shifting and pick up signals from adjacent muscles, and are sensitive to transient variables such as varying amounts of perspiration on the skin [61]. This can cause inconsistencies in the sensor data and pattern recognition results. Using sEMG for prosthesis myocontrol has not been accurate, robust or reliable enough to make the system practical for use by amputees [38, 59].

The most commonly used sEMG electrodes in the literature for controlling prostheses are the Ottobock's MyoBock 13E200 sensor [42]. The MyoBock sEMG sensors are bipolar electrodes that include on-board signal processing [4, 63]. These electrodes have also been used commercially for prosthesis control, but only for controlling basic, 1 or 2 DOF motions [1]. A commercially available prosthesis control system made by CoApt uses an array of bipolar electrodes that are incorporated into a custom fit prosthetic socket. The CoApt system includes advanced signal processing and pattern recognition software that makes it one of the most advanced prosthesis control systems commercially available [55]. Unfortunately, these systems remain out of reach to most consumers because they are extremely expensive, and still, the systems are not robust enough for regular use

by amputees [61].

2.3.2 Force Myography

Force myography senses the physical manifestation of muscle contraction, otherwise known as the volumetric changes associated with muscle activation/deactivation. Research of this myography modality is relatively new to the field of myocontrol, as the first work on FMG began in 1999, and has only really picked up since 2018, with the popularity of ML technology [8, 64]. In some applications to date, FMG has been found to be at more accurate than sEMG, but there are concerns that its usability is limited outside of the lab and on amputees [4, 61].

One type of FMG sensor is the piezoelectric transducer, which generates electricity when a force-induced movement occurs on the piezoelectric membrane. The amplitude of the signal generated is proportional to the speed of deformation of the piezoelectric membrane. Since this type of sensor only detects transient effects, it only accounts for a very small percentage of FMG research and has had limited success for prosthesis control [8, 65]. The most recent FMG development found in the literature is a subset of FMG called tactile myography (TMG) [66, 67]. TMG works by separating two electrodes with a semi-conductive foam. The resistance of the foam changes based on the pressure applied, thereby allowing force changes to be detected. It has a similar construction as a bipolar sEMG sensor, albeit with a different geometry and foam layer in between the electrodes, and requires custom hardware as it is still early in its development and is not commercially available. TMG has been used for offline prosthesis control with good accuracy and promising results [66]. Another type of FMG is the resistive polymer thick film (RPTF), which changes its conductivity based on the pressure applied to it. Two flat electrodes are separated by a semi-conductive polymer layer, so that when a force is applied, the overall output resistance decreases [68]. This type of FMG sensor accounts for 55% of the sensors found in the literature, which can partially be attributed to it being a compact and cost-effective sensor [8]. A major limitation of the RPTF FMG sensor is that it degrades over time, which limits the reliability of their measurements after days or weeks [8].

RPTF FMG sensors are very thin, flat sensors so to conform to the forearm and localize muscle volume changes onto the sensing membrane, researchers have found success by using rigid backplates and bumpers between the sensing membrane and the skin [4, 8, 63, 69]. The bumpers are usually either dome or cone shaped, and are made of semi-rigid materials. Bumpers have been successful because the shape and material concentrates the force exerted by the muscles onto the FMG sensing area. FMG bumper types and styles have not been formally investigated, but it is believed that these bumper membranes also contribute to signal stability since they behave as a mechanical filter [16, 69]. RPTF FMG sensors are commercially available, but in most scenarios, a custom FMG housing and electrode–skin interface needs to be built. Conveniently, this housing is often also used as the housing for the sensor's electronics [8]. Custom-built FMG control systems are often designed in the form of a band, with FMG sensors placed inside adjacent to one another with firm backplates for each sensor, and a bumper between the sensing membrane and the skin. Other groups have fit FMG strips into prosthetic sockets to test on amputees [65, 70]. Some bands and prosthetic sockets were made to fit over 50 FSR sensors, where they were able to detect up to 48 gestures with good accuracy, and using only 8 FSRs on the forearm achieved better accuracy than many sEMG configurations [24, 61, 71, 72].

As a newer myography method, the standards of signal processing, sensor configuration and application methods have yet to be standardized for FMG. An important feature is that because this modality senses pressure changes, FMG sensors also capture the weight of the sensing system as it presses against the arm. Furthermore, FMG can be affected by the prostheses weight they are attached to and any types of transient changes associated with balancing, accelerating, decelerating or even bumping into objects. Based on the signal itself, it is nearly impossible to distinguish between an external (from disturbance) and internal (muscle activation/deactivation) force [12, 73].

Typically these sensors are used in an array in the form of a matrix or a strap. For hand and wrist gesture recognition, this is usually in the form of a strap that goes around the bulk of the forearm — similar to sEMG. These bands are usually highly conformable to the user's limb shape and can be quite comfortable; but the band and sensors' flexibility introduces inconsistencies in the pressure applied to the forearm and FMG sensors. This can be compounded if the sensors are very tight against the skin and the force exceeds the linear range, and the corresponding voltage is not proportional. If the band is not tight enough, the sensors may shift within the device and along the arm, and it is difficult to ensure sensors are donned with the exact same

force, which may cause artefacts and signal inconsistencies. So far researchers have adjusted the tightness based on user feedback and comfort levels but this is inconsistent. Fortunately, easy-to-use software techniques that normalize/auto-scale the signal have been found to adequately mitigate some of these inconsistencies in a lab setting [8, 66, 74, 75]. Another concern with FMG is the between-subject variability. Muscle mass, limb size, skin thickness and fat percentage all affect the pressure signature felt by the sensor. This is especially true when the user is an amputee [8]. Even within subjects, variability has been found in the pressure signature before and after exercise with varying levels of fatigue. This can change day-to-day, and as such, researchers suggest incorporating other sensors such as sEMG to assess fatigue level, which is more useful information for a pattern recognition algorithm to decipher [8].

Although FMG has been used successfully for pattern recognition, RPTF FMG sensors have a non-linear response, large hysteresis, and long-term drift error associated with the degradation of the sensors. Also, because this modality detects muscle's volumetric changes, the sensors acquire a muscle activation signal after contraction, and thus is slower than EMG. The non-linear behaviour is addressed by selecting bias resistors that keep the voltage output within a linear range [8, 64]. The large hysteresis and long-term drift error are said to be of little concern in prostheses control applications because of the low force exhibited on them and the lack of large constant loads [8, 12]. These drawbacks are somewhat mediated, and sometimes superseded by the high signal-to-noise ratio and ease-of-use of these sensors [64]. Still, there are no commercially available prosthetic control systems that use FMG; and is likely, or at least partially, due to the sensor longevity concerns [8].

To summarize, some of the advantages of RPTF FMG sensors are their compact size, light weight, low power, low cost and high signal-to-noise ratio. Compared to sEMG, the signal is also significantly less complex, which also reduces the cost of any electronics necessary for the system to function. This opens up the possibility to more affordably use FMG sensors in bands or array configurations. Since FMG technology is cost-effective and allows for high levels of customization, the idea of using several sensors is often explored with the theory that using more sensors makes the system more robust [61]. RPTF FMG sensors are good at distinguishing hand and finger patterns, and like sEMG with modern pattern recognition techniques, don't need precise sensor placement [17, 24].

The main limitation of FMG development thus far is the lack of thorough research. Research groups working with FMG have achieved promising results, even with mapping dynamic tasks, but there are no commercially available prosthetic control systems based on FMG because it has several sources of unreliability [8, 76]. Two of the main factors affecting the reliability of FMG are the sensor limitations and the device configuration [8]. They are prone to deterioration over time, have hysteresis, nonlinear effects and slower response than sEMG. FMG is also sensitive to external forces such as mechanical disturbances and transient effects. Another concern with FMG is the donning pressure of the sensing system, as this can be a source of inconsistency without adequate mitigation considerations [16]. For the control of prostheses, these sensors may be limited to large muscle bodies that provide stable contraction and muscle definition [72, 77].

2.3.3 Inertial Measurement Unit

Inertial sensors, which are commonly found in smartphones, are of three types: accelerometers, gyroscopes and magnetometers. Together these are commonly referred to as IMUs. Accelerometers measure acceleration about the x, y and z axes. Since the force of gravity is always accelerating towards the Earth, gravity registers on an accelerometer. Gyroscopes measure angular velocity, or change in orientation about the x, y and z axes, and the magnetometer measures x, y and z positioning, relative to magnetic north [78]. Nowadays, most IMUs are based on microelectromechanical systems that are small, light, inexpensive and have low power consumption, making them easily integrated into wearable systems.

As mentioned, gyroscopes measure angular velocity, which is a unit over time. When the IMU is stationary, the gyroscope's values are near zero, making it a measurement that detects movement. This is important for measuring body kinematics to detect how the IMU and the system that it is attached to is moving. The accelerometer measures acceleration, which is also a unit over time, and is important for detecting acceleration and deceleration effects associated with moving, stopping and balancing. The constant downward gravity vector is also captured by the accelerometer, and can be extremely useful for determining the orientation of the IMU (or system that it is attached to) [30, 79]. Sensing the gravity vector has been very useful in prosthesis research as a way to

counteract the "limb position effect," which refers to changes in myography sensor signal due to positioning of the arm and/or orientation of the prosthesis system [12, 43, 80].

Orientation and movement detection gives a prosthesis control system more information about the system that it is measuring, so that a pattern associated with these effects can be considered when deciphering patterns. These sensors are important for measuring body kinematics, such as the compensatory balancing movements, limb orientation and even information associated with fatigue, smoothness and the velocity of limb movements [81]. These sensors are rarely used on their own for hand and wrist gesture recognition, as the kinetic and orientation information alone is not enough to find patterns associated with relevant gestures. They have been found to be extremely beneficial when combined with either EMG or FMG, and will be discussed further in the following section [8, 11, 12].

2.4 Multi-modal Myography

Individually, sEMG, FMG and IMU sensors have all been tried as natural and intuitive prosthesis control modalities, but have not satisfied the required accuracy and robustness criteria to be practical for amputees to use. Each sensor modality has its limitations that cause the system to not work adequately. By capturing redundant and supplemental information with various modalities, in theory, sensor limitations can be filled by another modality, thereby attenuating its limitations. For example, IMUs combine accelerometers, gyroscopes and magnetometers to make more robust motion and position measurements [78]. As an example specific to this application, combining inertial information with FMG adds arm orientation effects that can be used to decipher why a particular pressure signature is occurring on the sensing membrane so that the weight of the prosthesis can be considered [12]. As another example, FMG signals are known to be more consistent at separating muscle patterns, and a known limitation of sEMG is that its signal contains a lot of noise and senses the activation of adjacent muscles — so if sEMG is giving an indistinct muscle pattern, FMG could mitigate this problem and be more effective, or at least more consistent at deciphering the intended gesture [16]. The use of different kinds of sensors captures more of the variables associated with what is happening with the system of interest. Though some of the
information collected may be redundant, it may still be useful to validate and increase consistency of the prosthesis control system's pattern predicting ability.

As mentioned, individually these sensors have their limitations, but there is a growing field of interest in combining these modalities to create more robust sensing systems for pattern recognition models to utilize. Many recent papers on modern prosthesis myocontrol push for multi-modal control schemes [4, 8, 11, 14]. All of the texts report improvement when using multiple modalities, whether in accuracy or robustness. Potential challenges of multi-modal myocontrol are the increased amounts of information processing required, and the complexity of integrating all of the sensors into a single system. These are challenges that need to be considered and overcome for the feasibility and effectiveness of a multi-modal system to be used for prosthetic control systems.

2.4.1 sEMG+FMG

To combine sEMG and FMG, most researchers use the commercial Ottobock EMG and Interlink 402 FMG RPTF sensors, and integrate them into an arm band or prosthetic socket [4, 8, 63]. Some groups integrate the sensing system by co-locating the sensors, some alternate the sensors, and some have each modality on separate bands [7, 61, 82]. Co-locating the sensors gives the best way to compare the sensing modalities since all of the sensors share similar points of contact on the forearm. Also, because useful surface area of the forearm is limited, using one band where each sensor housing contains both modalities utilizes this space more efficiently, especially since these modalities are affected by their contact with relevant muscle features [8, 83]. Jiang et al. [83] used co-located sensors and achieved a consistent 10% accuracy improvement by using the two modalities simultaneously over using just one modality. Whereas a group who did not have colocated sensors had insignificant accuracy improvement, but had robustness increase by combining FMG+sEMG [4]. No matter the integration technique used, the literature points in the direction that multi-modal is required to drive the field forward [14, 61, 83]. In some cases, FMG was found to be nearly as good as FMG+EMG, so it is debated whether there is a need for EMG, but overall, many agree that multi-modal data adds consistency and accuracy to transient control — a much more difficult task than gesture classification [4, 24, 82]. Consistency improvements are critical for out-of-lab scenarios because of extra variables that are introduced in out-of-lab scenarios. It is recommended that multi-modal systems be used for myocontrol of prostheses — especially for transient control [16].

What makes FMG+sEMG so enticing is that it detects both the electric and volumetric phenomena associated with muscle contraction. sEMG has quick detection, robustness to arm position changes, and sensors that last a long time. These characteristics can mitigate the slower response time, force distribution changes with motion, and deterioration of the sensor over time observed with FMG. FMG has better gesture separation, is cheaper, and requires much less data processing, which can offset sEMG's cross-talk concerns, computational and monetary costs. Co-located sensors are recommended to ensure that both sensors are placed on the same critical muscle bodies [83, 84].

2.4.2 sEMG+IMU

The modality combination most experimented with is the combination of sEMG+IMU, which can be found in a couple commercial systems. The Trigno, made by Delsys, uses 10 wireless sEMG sensors with on board signal conditioning, and 3-axis accelerometers on each sensor board [80, 85]. Another commercial system is the Myoband, by Thalmic labs, which uses 8 wireless sEMG sensors with a 3-axis gyroscope and accelerometer [11, 86]. Having these systems commercially available is a testament to the benefit of this combination, and how it is the most researched modality combination.

For custom sEMG+IMU systems, Krasoulis et al. [87] conducted an analysis on how many sensors were required when using sEMG versus sEMG+IMU and found that by combining modalities, they could reduce the overall number of sensors required and improve real-time performance. The main benefit of combining these modalities is accuracy improvement, although robustness increases are not discussed nearly as much as with sEMG+FMG. Accuracy improvements are attributed to the IMUs ability to provide information about the orientation of the arm and any potential movement happening. With the IMU data, the pattern recognition algorithm has the information necessary to make any connections between position/orientation effects and its relevance to any sEMG signal changes [43, 88].

Groups using pattern recognition for prosthesis control have found success by combining sEMG

data with accelerometer and gyroscope data, but groups have also found found accuracy improvements while omitting gyroscope data [43, 80]. This is likely because for static gesture recognition, the raw gyroscope data does not give additional information about the gesture being held, while the accelerometer provides critical orientation information through the gravity vector.

2.4.3 FMG+IMU

As a newer modality combination, there are no FMG+IMU integrated systems available commercially. There are commercial FMG and IMU sensors that researchers have integrated themselves, such as Ferigo et al. [12], who integrated FMG array strips and an IMU into the prosthetic socket of an amputee. The small form factor of the FMG sensors allowed the group to use over 50 FMG sensors and integrate the IMU. This combination was found to be very successful in classifying gestures, as it was able to mitigate the limb position limitations of using FMG sensors alone. The limited work on FMG+IMU to date claims that this combination is enough to adequately classify gestures, as they have achieved 99% accuracy; however, when dynamic tasks were added to the pool, only 86% accuracy was achieved, which is not surprising since FMG sensors have varying success with dynamic tasks [12]. Again, this is attributed to FMGs sensor limitations and working principle which captures pressure changes on the membrane, detecting volumetric changes of the muscle, but also the weight of the prosthesis against the arm, and pressure changes associated with movement. Nonetheless, it appears that by combining FMG+IMU, the limb orientation effects that hinder FMG, are attenuated by the inclusion of orientation data [72].

2.4.4 FMG+EMG+IMU

Integrating FMG+EMG+IMU into a device for prosthesis control was found only once in the literature. Carbonaro et al. [17] integrated these three modality types using commercially available sensors into a rigid forearm brace. More specifically, they used 8 RPTF FMG sensors, 2 Ottobock sEMG sensors and a standard IMU. Interestingly, the group did not try pattern recognition algorithms to decipher the myography signals, but instead opted for a logical control system that used both sEMG and FMG threshold values for grasp and release detection, and the IMU for position detection [17]. They tested the hardware on 10 healthy subjects and were able to get a 90% success rate for completing a predefined task. Unfortunately, being a preliminary study, this work was limited as there was no analysis done or statistical significance found.

2.4.5 Conclusion

In theory, integrating all three sensing modalities would capture redundant and supplemental information about what an amputee is intending to do with their hand/wrist. This is important for HMIs in general, because all of the myography methods available are imperfect, and are limited in various ways. Robustness and accuracy improvement have consistently been reported in the literature when combining two sensor modalities, so it is possible that even better performance can come from combining three [4, 8, 46]. Prior work has also highlighted other benefits of using multiple sensor modalities, such as the need for fewer sensors, which can help with financial and computation costs.

Integrating all three sensor types into a single prosthesis control system with pattern recognition has not been found in the literature. Exploring the fusion of FMG+sEMG+IMU with pattern recognition is novel, and with that there are a lot of unknowns to explore. A probable downside of such a system is that it will likely be difficult and complex to integrate the multiple sensor systems into a compact, wearable device, as integrating two has been complex [4, 13]. Other potential issues could be that having data from three separate modalities, may make the system highlight the weaknesses of each modality instead of the strengths, and that it will be more computationallyexpensive — although this may be mitigated by being able to use fewer sensors [4, 8, 89]. The actual benefits and downsides of integrating the three are unknown, but the theory and research success of using two modalities leaves the question of a strong framework to explore: namely, whether using three sensing modalities makes the system even more robust and accurate, economical and likely to be adopted by amputees.

2.5 Data Set Creation

To use myography sensors for controlling an advanced prosthesis, raw sensor values need to be processed so that they can be more readily deciphered by a pattern recognition algorithm. First, the myography data needs to be captured, organized and, for offline analysis, saved. To give the classification algorithms the best chance at accurately mapping signal patterns to gestures, the raw myography signals need to be filtered and segmented, and useful features extracted from the signal values [43, 90]. This section will investigate the state-of-the-art methods used to create data sets for use with pattern recognition algorithms for prosthesis control systems.

2.5.1 Signal Acquisition

To use the data from myography sensors for a prosthesis control system, the sensor signals need to first be captured so that they can be processed and then interpreted. For many commercial sEMG and sEMG+IMU systems, this comes in the form of a corresponding application programming interface (API) for the sensors [91]. For custom systems, such as those with FMG sensors, custom solutions need to be created. These solutions often include microcontrollers such as Arduinos and data acquisition (DAQ) cards that can capture signals from the sensors [4, 63, 81, 83].

Common among all of the data capturing devices are analog-to-digital converters, which sample the analog, continuous data from the sensors, and convert it to a digital, discretized representation. The sampling rate is the rate at which the continuous signal from the sensors is being measured and is a very important consideration when collecting sensor data onto a computer. To capture phenomena from a sensor using an analog-to-digital converter (ADC), the sampling rate must be quick enough to capture the phenomena that occur at certain frequencies [8]. The Nyqvist Criterion is a rule that states that sampling frequency must be at least twice the highest frequency of the phenomena to be measured, which is different for each myography modality [43].

As mentioned in the myography section, EMG has been around for quite a while, and its energy distribution has been established to be within the 0–500 Hz range [58, 92]. According to the Nyqvist Criterion, the minimum sampling frequency for sEMG must be 1000 Hz, but many custom systems and the commercially available Trigno, use 2000 Hz as the standard sampling frequency [24, 85, 90, 92]. FMG is less established, and the minimum sampling frequency is still debated. Xiong and Quek [93] state that 4.5 Hz is the maximum frequency of human hand motions, and thus recommend 10 Hz as the minimum sampling frequency [24]. A more recent study by Menon et al. [64] looked at FMG minimum sampling frequencies required for different ADL tasks to ensure that the content of the signal is not compromised. For isometric and dynamic conditions, they recommend minima of 58 Hz and 84 Hz respectively [8, 71]. Groups who have taken a more conservative approach use higher sampling frequencies of 100 to 1000 Hz for FMG signal acquisition [9]. Since FMG is newer, there is also more variation among custom FMG setups — with the addition of backing plates and bumpers — so in order to accurately capture relevant phenomena, it is likely better to use higher sampling frequencies.

2.5.2 Signal Filtering

After the signal is digitally acquired and saved, the signal must next be cleaned for unwanted information captured by the DAQ card. Signal filtering is the process of removing unwanted artifacts, such as electrical and environmental noise from the signal of interest [43]. The purpose of this process is to maximize the signal-to-noise ratio and minimize distortion of the signal [51, 58].

EMG is a fairly weak signal and is greatly affected by noise from surrounding electronics, shifting electrodes, data lines, ambient noise, and electromagnetic radiation from the environment [11, 46]. The energy distribution of EMG ranges from 0–500 Hz, with the dominant components being in the 50–150 Hz range [58]. Anything outside ranges from 0–500 Hz can be considered unwanted noise and should be filtered out before proceeding to later stages of processing [51].

Although the energy distribution of EMG is between 0–500 Hz, 20 Hz high-pass filters are often used because anything below 20 Hz could be caused by motion artifacts, which is a large source of noise for EMG. Frequencies above 500 Hz are filtered out using a low-pass filter [46]. To carry out the filtering, the most popular filter is a 4th-order Butterworth filter [11, 59]. Using a 4th-order Butterworth bandpass filter successfully reduces noise and keeps the useful information in the signal [11, 51, 58]. Sometimes the sEMG signal is biased, and has been noted to affect performance [46]. This unwanted feature can be easily filtered out of the signal by subtracting the mean of the signal from the signal [59].

Sometimes a notch filter is also used to remove noise that comes from power lines — which in North America this is in the 50–60 Hz range [11]. Note that the most important EMG information lies within the 50–150 Hz range. Since there is no ideal notch filter that can remove noise at only 50 Hz or 60 Hz — it would always remove more of the bandwidth — many groups have opted to leave the power line interference since it will conserve useful EMG information. Therefore, a notch filter is not recommended for EMG data processing [46, 58].

FMG and IMU accelerometer and gyroscope signals have been used unfiltered because they have acceptable signal-to-noise ratios [12]. Furthermore, using bumpers on RPTF FMG membrane naturally filters the signal by mechanical processes and is often used without any additional signal filtering [8, 94].

2.5.3 Signal Segmentation

After unwanted information from the sensor signals is filtered out, the data must next be segmented into sections of time, a process known as windowing. A signal window has at least two data points and often has more. Windowing the signal is important for the next signal processing step, which will be to find underlying features of the signal. Signal segmentation/windowing has been thoroughly investigated for sEMG, so naturally, FMG research has started by trying the successful sEMG windowing methods [61]. The optimal windowing procedure is a balance of window size, measured in time, and overlap between adjacent time sectioned windows. It has been found that window length is proportional to classification accuracy, but longer window lengths introduce greater controller delays — overlapping windows is a technique that allows for larger window lengths to be used with less delay [3, 80, 82].

For real-time prosthesis control, a constraint is that the window length must be less than 300 ms, as this is the maximum acceptable time delay. If the prosthetic system takes longer than this to react to a user's input, the system becomes frustrating for a user to use [18, 29]. Thus, 200 ms to 250 ms window lengths have become widely used by prostheses control researchers, with some also including a 25 to 75% overlap so that there is less of a time delay between subsequent windows, allowing for even faster response times [11, 40, 59]. These values were found to be a good balance between accuracy and an acceptable prosthesis response time.

2.5.4 Feature Extraction

After the windows have been segmented appropriately, the window-based features must then be calculated before use with a pattern recognition algorithm. For real-time, out-of-lab use, it is important that the features and pattern recognition models both work well enough, but also be quick enough, in low power computational platforms [43, 90]. Extracting features from signal data is critical for using myography modalities with pattern recognition algorithms. Extracting signal features can break down each sensor channel into relevant attributes that can be used by the pattern recognition algorithm to decipher a pattern.

Features from a digital signal can be extracted in the time-domain, frequency-domain or both. Time-domain features are typically less computationally-expensive — and fortunately when using sEMG for prostheses control — have been found to out perform time-frequency and frequencydomain sets [11, 43, 46, 52, 95]. Using time-domain features for IMU and FMG has also been successful [4, 8, 11]. There has been extensive research conducted to find the best features for distinguishing EMG signals for classification and some of the most used time-domain features are listed below [11, 96].

Mean absolute value (MAV): MAV is one of the simplest and most often used features out of all window-based features [11]. This value is the rectified mean amplitude of the signal over the window length, and is calculated as:

$$MAV = \frac{1}{N} \sum_{i=1}^{N} |x_i|.$$
(2.1)

Mean absolute value slope (MAVs) reflects the trend of the signal, and is calculated by finding the difference between the MAV of two adjacent time periods. This feature can be useful, but it cannot be used for real-time applications [46].

Waveform Length (WL): WL measures the cumulative length of the waveform within the window segment [97]. This value reflects the variability and frequency of the signal, which gives an indication of the signal's complexity in that window. It is calculated as:

$$WL = \sum_{i=1}^{N-1} |x_{i+1} - x_i|.$$
(2.2)

Autoregressive Coefficients (AR): AR coefficients are found by fitting the data points within window length to a linear combination, plus a white noise error term [11]. The coefficients of this linear combination are used as the calculated feature. The 4th-order AR has been suggested as the most suitable, and has been used in previous work [30, 46, 59]. *p* is the order of the AR model, and the AR model is defined as follows:

$$x_i = \sum_{p=1}^{P} a_p x_{i-p} + w_i.$$
(2.3)

Zero Crossings (ZC): ZC is found by counting the number of times the signal crosses the zero axis (with minimum threshold) within the window length. This feature is a reflection of the frequency of the signal over the window length [11, 96]. The ZC value is computed as follows:

$$x_i = \sum_{i=1}^{N-1} f[x(i), x(i+1)], \qquad (2.4)$$

$$f(x,y) = \begin{cases} 1, & \text{if}(x \times y) \cap |x - y| \ge \text{threshold} \\ 0, & \text{otherwise.} \end{cases}$$

sEMG is a very complex signal, and finding distinct features from each window helps the pattern recognition algorithm decipher the signal and find patterns more consistently than by just using the raw signal [59]. The most commonly used and successful features for sEMG classification are MAV, WL, ZC, AR, and MAVs as highlighted in a comparison study by Phinyomark et al. [96], and validated by Campbell et al. [35] and other sworks [11, 46].

Some FMG features have been used with success, but the applications are very specific and do not overlap with upper limb prosthesis control [64]. For upper limb prosthesis control, FMG features are often not used at all as they do not seem to be critical. The most consistently successful FMG information used for pattern recognition is simply the raw value or MAV of the signal. This is likely due to the steady and high signal-to-noise ratio of the FMG signal. For IMU, raw signals or the MAV are also the most often used [43, 80, 98].

2.6 Pattern Recognition Methods

Data from the sensors is filtered, segmented, and features are extracted from the signal to provide a pattern recognition algorithm a better chance at being able to parse and find connections between input signals and particular gestures [43]. The pattern recognition algorithms use training data, which is composed of input columns of the various processed sensing data and features. With the training data, the algorithm is also given the output, in order to train the model to output that value when it sees the associated patterns. To test the trained model, only the input data is given and the model is used to predict the output — as would be done when the system is trying to predict an amputee's intended gesture with processed data from muscle inputs. There are several pattern recognition models used for this application. Below are some of the most successful and used ones.

There are two main categories of ML, pattern recognition algorithms, which are referred to as classification, and regression models. Classification models are used to predict discrete gestures from input signals, such as looking at the EMG, FMG and gyroscope signals at a discrete time step, and predicting which hand gesture the user may be doing at that instant. Regression models are used to predict continuous/transient states, such as the trajectory of the hand and wrist [8, 52]. Regression modelling has the potential to give the user proportional speed, force and transient control of their prostheses, similar to how people control their natural limbs. Prosthetic control systems that have been tried on both classification and prediction of regression/continuous states have consistently performed worse when predicting transient states, as prediction is much more difficult [4, 43]. The ideal eventual outcome for prostheses control systems is to allow the user real-time prosthesis hand/wrist gesture control as well as proportional speed and force control that will allow them to perform their ADL.

2.6.1 Artificial Neural Networks

Artificial neural networks (ANNs) are a broad class of ML algorithms used for pattern recognition and classification. They are known for their ability to have high generalization over large data sets that are not linearly separable. ANNs are based on layers of interconnected activation functions and nodes (neurons), that attempt to build complex relationships between the input data and, in the training stage, a known output. Input data percolates through the interconnected layers, assigning neuron weights, and then the output data goes through the layers from the output to input, adjusting the weights to further minimize the classification error. To minimize the error, various optimization techniques, such as gradient descent, can be used to minimize the classification error on the training data [8, 52]. These algorithms are highly configurable and there are numerous techniques to auto-optimize to find the best performing combinations. Important, tuneable hyperparameters are the number of layers between the input and output layer (called hidden layers), number of neurons in these layers, batch size, optimization loss function, the activation function present in the hidden layer neurons, and the number of epochs used to train the model [8, 11, 99].

ANNs have been used to classify sEMG fusion gestures with 85–91% classification accuracy [11, 99]. ANNs have also been tried with FMG+IMU for dynamic grasp and release detection, achieving 92.67% average classification accuracy [30]. They are a popular, often successful method used in offline gesture classification analysis, but because of their complexity, they are not as popular a choice for online/real-time pattern recognition/prosthesis control.

2.6.2 Support Vector Machines

A support vector machine (SVM) is another ML algorithm used for classification that is very useful for solving nonlinear pattern recognition problems. SVMs works by taking input data and finding an optimal hyperplane between the different class outputs. Distinct hyperplanes are established to separate data points into different classes. An optimized hyperplane is calculated based on the separation distance created by the data points in each class. The algorithm attempts to maximize the separation distance (classification margins) while minimizing the number of classifications that get placed within the margin. Within the margin, the algorithm also attempts to maximize the separation distance from the centreline. Originally used to separate two classes, SVM has evolved to be used for multi-class separation by using kernels to project the input data into higher dimensional space. This transformation helps group data that are similar so that the hyperplane can separate the data accordingly. The kernel is referred to as gamma, and defines how influential the individual points are in creating the location of the hyperplane. The kernel's degree and coefficients are all important aspects that are configurable, tuneable and can be optimized. This model development can be computationally-expensive, but is not as expensive as ANNs, and with modern processing is used in real-time applications [11, 97, 100].

SVMs have been successfully used for many EMG applications including motion classification for the control of wearable devices [100, 101]. Using SVMs with muscle activation information from sEMG sensors, Omario et al. [102] achieved 81–91% classification accuracy and Englehart et al. [94] achieved an accuracy of 92% in a real-time experiment. For FMG it has even been found to have superior performance compared to other pattern recognition algorithms [8]. Combining modalities, using 2 sEMG and 37 FMG sensors on an amputee resulted in a classification accuracy of 94.8% for 4 gestures and 81.6% for 6 gestures [82]. In another study on 22 healthy participants that used the commercially available Myoband (EMG+IMU), SVM was the best performing classification method with 82.4% accuracy [11, 99].

SVM is the second most used classification algorithm and is touted as one of the best for EMG classification [11]. It is also the predecessor to the most often used regression pattern recognition algorithm for prosthesis control, the support vector regression (SVR) algorithm, which makes SVM enticing for building onto for future work [8].

2.6.3 Linear Discriminant Analysis

Of the classification algorithms mentioned thus far, LDA is the most straight forward, computationallyefficient model [82]. The LDA algorithm searches for linear combinations of input variables to find the linear combination that best separates each class using its covariance [103]. As it is a very simple algorithm, it is also not very customizable and cannot be optimized for more difficult scenarios.

A study using two sEMG sensors with 37 FMG sensors on an amputee to classify 3 gestures achieved 94.8% accuracy, and 81.6% for 6 gestures (the same as SVM for the same study) [82]. Interestingly in FMG studies it was also found that there was no statistically-significant difference between SVM and LDA classification results [8]. In a study using co-located FMG+sEMG to classify 0–9 in American sign language, Jiang et al. [83] was able to achieve 91.6% classification accuracy. In another study using eight sEMG electrodes and an IMU to classify 3 gestures in 5 arm positions, Geng et al. [104] achieved an accuracy of 90%. By combining 43 FMG sensors with an accelerometer on an amputee, Ferigo et al. [12] were able to obtain 86.3% accuracy for classifying 11 gestures. LDA has been successfully used for offline and online gesture classification, but its lack of customizability and regression counterpart makes it limited for future development.

2.6.4 Regression

Instead of interpreting the intent of the user as a discrete grasp/gesture, with regression models the algorithms are tuned to transient effects, such as level of muscle activation, speed of contraction, amount of force and path prediction. This type of control is significantly more akin to controlling a biological limb and is an important capability for prostheses control technology, but is more difficult to predict and hasn't performed adequately with single and paired modality prosthesis control systems [4, 96, 100, 105–107]. Regression models were not researched in depth and are left for future works because the benefits of combining three sensing modalities for prosthetic control has yet to be discovered. When sensing modalities are first tested for this application, typically their discrete gesture classification accuracy is assessed to determine whether the modality combination provides any benefit, and then regression control algorithms are tested as the next step [15].

Sensor fusion combinations have the potential to solve the minimum accuracy requirements and address the main complaints by amputees, which is the lack of robustness of the system outside of the lab setting [29]. Castellini et al. [4] tried trajectory prediction by combining FMG+sEMG and had good results with the two modalities responsible for a significant improvement in their results, but claim that the results were not robust enough for out-of-lab scenarios. They strongly assert that multi-modal is a necessary forward step in this domain, as it has been found to provide pattern recognition robustness by way of some sensors compensating for the limitations of others, and has the potential to fill the need to use with transient prediction type [4, 14, 16].

2.7 Conclusion

There are important activities of daily living that a prosthetic system must be able to do in order to be functional for an amputee. The prostheses themselves are not the limiting factor to this, but the technology used to control the prosthetic system. Myocontrol is the field of sensing biological signals of the body, and using them with pattern recognition algorithms to give amputees control of their prostheses as though it is a natural extension of their body. Unfortunately, the systems developed to date have not been able to meet accuracy and robustness requirements for the system to be readily adopted by amputees. To increase the reliability of these systems, researchers are combining myography modalities, with the theory that by having multiple myocontrol modalities, they can fill the gaps where other modalities are lacking, and to give a the pattern recognition algorithm more complete information from which to associate gesture or movement patterns to [108].

Most of the methods of sensor fusion for this domain have included pairs of sensing modalities, but only one preliminary work has been published on combining three modalities. To assess the effectiveness of combining three sensing modalities, it is critical to use co-located sensors and state-of-the-art signal processing, data preparation and classification algorithms to properly analyze performance and compare it to other modalities and in-lab benchmark testing. It is also important to recognize that the system will likely perform worse in real-world, out-of-lab scenarios [4, 13, 79].

To reach the point where these systems can be used by amputees in real-time, prosthesis control systems need to be consistent at interpreting what the user is intending the prosthetic system to do, and do it quickly, consistently and affordably enough for the system to become more widely adopted [18]. ML pattern recognition algorithms with multiple-myography modalities as inputs are critical for achieving this, as researchers have made large strides by using these technologies. Once adequate real-time classification results have been achieved by amputees, regression control and task-oriented assessments should be used as the final metric of an all-encompassing prosthetic control system.

Chapter 3

Data Collection

This chapter describes the equipment and procedure used for collecting FMG, sEMG, and IMU data from participants while they performed the gestures important for ADL. The main objective of this experiment was to conduct a proof of concept of a custom data-collection system, and determine if using three myography sensing modalities can improve the classification accuracy of muscle activity associated with the ADL. Improvements would mean more accurate and consistent control by increasing the ability of a pattern recognition algorithm to classify the sensory data associated with performing hand and wrist gestures in different arm positions. Sensory data were collected from the dominant arm of able-bodied subjects while they performed prescribed wrist and hand gestures. A custom multi-modal sensing device needed to be created for this work; design considerations and how the system was integrated will be outlined. The participant recruitment procedure, and experimental protocol for data collection will also be outlined in this chapter.

3.1 Equipment

A system that integrated FMG+sEMG+IMU into a single system did not exist commercially, and thus a custom device needed to be researched and developed for this work. The system developed and used for this work can be seen in Figure 3.1. To test the hypothesis that using three simultaneous sensing modalities brings accuracy and robustness improvements, the hardware needed to be chosen carefully — as to be considered state-of-the-art work, the sensors and implementation needed to meet existing benchmarks. This section will go through the design considerations and device design. Major considerations for the design were compactness (small form factor for wearable systems), affordability, signal clarity, and ease-of-use.



Figure 3.1: The multi-modal arm band that was designed and used for this work.

3.1.1 FMG Design Considerations

Using FMG for myocontrol is a relatively recent development, and thus the state-of-the-art configurations are not well established. What is known is that the force sensing resistors (FSRs) produced by Interlink Technology are the most popular and one of the most affordable FMG sensors used [8]. These sensors have a sensitivity of 0.1 N and can measure up to 20 N, which is well within the range of forces generated by a contracted muscle pressing into the FSR [8, 68]. FSRs have been used in various configurations for myocontrol/gesture recognition with accuracies reported over 90% [16, 72, 76, 109].

To find an effective configuration for this work, a one subject experiment was conducted to test various sensor configurations using the Interlink FSRs. All of the tested configurations used FSRs placed within in a removable arm band. Within the arm band, the FSRs had either no support material, a rigid backing plate, a bumper extension on the FSRs sensing membrane, or both the rigid backing plate and bumper extension. An unmodified FSR, and modified version of the FSRs with backplate and bumper can be seen in Figure 3.2. FSRs were built into these configurations



Figure 3.2: A commercially-available Interlink 402 FSR in two configurations: (a) without modifications, and (b) with rigid backplate and cylindrical bumper modifications — the best performing FSR configuration.

and then tightened around forearm similar to where a myography arm band would be located — around the largest bulk of the forearm. The subject was asked to clench their fist, and the FSRs' response was recorded and compared. The goal of this experiment was to test which FSR configuration was the most sensitive to the forces exerted circumferentially into the arm band by the contraction of the muscles of the forearm.

From the results, the most consistent and sensitive FMG configuration was the FSR with a rigid backplate and bumper. A prototype version of this configuration can be seen in Figure 3.2. This configuration likely worked well because FSRs are flexible, and when a user contracts an underlying muscle, if the FSR is pressed into a deformable arm band that offers minimal opposition, much of the axial force generated by the contracting muscle is dispersed into stretching that band. By having a rigid backplate between the FSR and arm band (behind the FSR), axial forces generated by the volumetric changes associated with muscle contraction are concentrated onto the FSR. Further, by using a protruding bumper on the FSR's force sensing membrane helps to concentrate the force generated onto the sensing membrane of the FSR.

3.1.2 sEMG Design Considerations

For sEMG, several commercial options were available such as the Trigno, MyoBock electrode, and Myo-Armband, but these sensors were ruled out for several reasons, including their lack of customizability. To use the Myo-Armband, a separate FMG band would need to be used, or for the Trigno and MyoBock sensors, FMG and sEMG sensors would need to alternate, wasting vital space on the limited surface area of the important muscles on the forearm. The Trigno and MyoBock sensors also have prohibitive costs for the average user, and all three commercially available options would not allow for co-locating FMG sensors and sEMG electrodes. The ability to co-locate FMG and sEMG sensors was important to maximize the use of the forearm's limited surface area, and because having the sensors in the same location is a more effective way to compare the modalities.

A critical feature of the sEMG system design was the electrodes. Many different electrodes were examined, with important considerations being that they needed to be medically safe, good conductors, easy to use, and relatively inexpensive. Gelled electrodes were ruled out because they make the system inconvenient to use by either needing to be replaced, or cleaned and gelled after each use. Ease-of-use and affordability were important requirements of the system, and thus dry electrodes were deemed ideal for this work. Commercially-available dry electrodes were surveyed based on material, geometry and cost. The electrodes used in the commercially-available CoApt prosthesis control system were found to be the most appropriate as they were made of stainless steel, which is safe for medical applications, and provide good conductivity [55]. The geometry of the CoApt electrodes was dome-shaped/convex and pushed onto the surface of the skin. By using convex sEMG electrodes that depressed the skin, the surface area of the electrode-skin interface increased, and was conducive to better conductivity at the skin–electrode interface. This was important in order to satisfactorily register MUAPs, and to partially mitigate a limitation of dry electrodes, which was their limited conductivity when compared to wet electrodes. Convex sEMG electrodes are also beneficial because they push into the superficial layers of skin, allowing the electrode to get closer to the muscle body where the MUAPs are generated and making signal detection more robust. These electrodes were also chosen because they were already used in a commercial product, which was a good indicator that they had been validated. For the sEMG system designed for this work, the electrodes were the most expensive component of the system, and for future versions will need to be addressed. The high cost of the electrodes was deemed to be an acceptable expense for this stage of development because they were commercially-validated electrodes, and once the system is better understood, could be optimized for cost.

A custom sEMG electrical system was chosen and developed based on the electrical designs by Wang et al. [58]. This system detects MUAPs (akin to muscle activation) on the surface of the skin, and then amplifies them using a differential amplifier. The signal from the differential amplifier was extremely noisy and in the tens of microvolts, so the sEMG signal was filtered and then amplified again to give a cleaner, larger signal that was akin and proportional to the muscle activation below the electrodes. The sEMG electrical circuit was first implemented onto a breadboard, its ability to detect MUAPs tested, confirmed, and was then used as the sEMG circuit to be implemented into the multi-modal system.

3.1.3 Multi-modal Integration

When integrating FMG, sEMG and IMU sensing modalities into a single device, form factor was a critical consideration that was challenging to implement. The components that needed to be integrated into the wearable were the commercially available FSRs, dome-shaped stainless-steel electrodes, IMU, and relevant circuit components including amplification and filtration hardware. All of the circuitry and components needed to be compact enough to be integrated into a wearable device that fit onto the forearm of a user, so all of the electronic components chosen were surfacemount to conform to the small form factor. The circuitry for the FMG and sEMG systems was combined into a single 50 mm \times 20 mm printed circuit board (PCB), as can be seen in Figure 3.3.

The PCBs were assembled using a reflow oven in order to robustly assemble the small components. All of the traces and connections were tested and faults addressed following a robust test plan that ensured that each system was working as intended. After the PCB passed the testing process, the PCB was affixed to the opposite side of a backplate, which can be seen in Figure 3.4. These sensor-module backplates were designed and 3D printed to contain two sEMG electrodes and an FSR in between. The perimeter of the backplate contained loops that allowed for an adjustable velcro strap to loop through. The strap was used to securely fix the arm band to the user and make it adjustable for different arm sizes. This design also allowed for the number of arm band sensor backplates/modules to change.





Figure 3.3: Integrated FMG, Figure 3.4: 7 sEMG and IMU PCB r before the electrodes s were assembled.

FMG, Figure 3.4: The configuration on the left is an assembledJ PCBmulti-modal arm band module without the enclo-
sure attached, and the module on the right is the
completely assembled module.

Four of these co-located sensors modules were used for a single arm band. A fifth co-located sensor also included the IMU and its relevant circuitry. The IMU chosen was the SparkFun 9 DOF IMU Breakout (LSM9DS1), which has a 3-axis gyroscope, 3-axis accelerometer, and 3-axis magnetometer in a small breakout board. The IMU was soldered to the fifth sensor module, and then all of the modules were enclosed by a cover to protect the electronics as can be seen in Figure 3.5. A block diagram of the entire data collection system can be seen in Figure 3.6. The system runs on 5 V, and consumes approximately 0.23 A. It can be seen in Figure 3.7.



Figure 3.5: Exploded computer aided design (CAD) view of a multi-modal arm band module with labelled components.



Figure 3.6: Block diagram of the FMG, EMG, and IMU data collection hardware. FMG and EMG data is collected from the multi-modal arm band, and then via a shielded wire to the National Instruments (NI) 9205 DAQ card for ADC. The IMU data is digitized on board, so it it sent via simple twisted wire pairs where it is decoded by an Arduino.



Figure 3.7: Complete multi-modal arm band system. From left to right: power supply, DAQ hardware wired to the completely assembled multi-modal arm band.

3.2 Signal Acquisition

3.2.1 Participant Recruitment

Trials using the custom multi-modal arm band began following approval from the Human Research Ethics Board at Western University (Appendix A.1). Participants were recruited via physical and email advertisement. Only healthy subjects over the age of 18 years old, with no previous upperbody injuries or neuromuscular deficiencies were considered for the trials. These exclusion criteria were implemented because musculoskeletal and neurological injuries or disorders could limit/affect the subjects ability to perform the gestures, and would introduce another variable to the study.

3.2.2 Experimental Protocol

Upon arrival at the laboratory, participants were given a copy of a consent form to review, which outlined the experiment requirements. Following participant consent, each participant provided information about their age, dominant hand, sex, gender, hours per week of physical activity, upper limb injuries, and whether they did any particular upper limb activities (i.e., rock climbing or weight lifting). Next, the investigator measured and recorded the subjects' forearm circumference, and bicep and tricep skin-fold measurements using a cost-effective arm-fat measurement technique found in the literature [110, 111]. Only a portion of this information was used for this study, but the subject information was collected because it could account for anatomical differences in myography signals that may be useful for future work. A summary of the participants' information can be found in Table 3.1.

Table 3.1: Summary of participant information.

Sex	Dominant Hand	Age (years)
16 Male	22 Right	25.0 ± 4.6
7 Female	1 Left	

3.2.3 Multi-modal Device Placement

To ensure consistency in the myography readings, the multi-modal arm band was placed in a similar location for every participant. Participants were asked to flex the wrist of their dominant hand in order to localize the flexor carpi-ulnaris muscle using palpation techniques, and then the IMU board was placed over it. The arm band was always placed in the same orientation, so the adjacent board modules were placed in similar locations. Longitudinally, the arm band was placed around the part of the forearm with the largest bulk, roughly one-third of the length of the forearm distal to the olecranon process (elbow). The velcro straps of the arm band was used to affix the wire to participants' lower forearm as per Figure 3.8, in order to mitigate movement restriction and relieve tension on the interface between the wire and multi-modal arm band. The device was then powered and left to idle for two minutes, as recommended by Nazmi et al. [112] in order to give the sEMG electrodes time to settle, and sweat to develop at the electrode–skin interface.

Next, a Matlab data collection program was started, and live sensor data were displayed on the screen. The participant was asked to flex and extend their wrist to determine if the FMG and sEMG sensors were sensing and transmitting data correctly. To ensure that the IMU was working, participants were asked to move their arm, and the accelerometer and gyroscope measures were monitored to ensure that they corresponded with the participant's movement.



Figure 3.8: Multi-modal arm band affixed to a participant's forearm, with the data wire affixed close to the wrist in order to relieve wire tension and mitigate movement restriction caused by the wire.

3.2.4 Data Collection Procedure

After the initial setup, participants were asked to follow a randomized combination of hand/wrist gestures and arm position prompts displayed on the monitor while sensor data were collected. An image of the gesture hold and rest prompts can be seen in Figure 3.9. The gestures were wrist flexion, wrist extension, wrist pronation, wrist supination, hand closed (fist), hand open, and precision pinch, as shown in Figure 3.10. All of these gestures were performed in a low, medium, and high arm position, corresponding to the upper limb at full extension (0°), arm at 90°, and arm at 135°, respectively, as can be seen in Figure 3.11. The gestures chosen for this work were based on critical gestures for ADL and used for previous prosthesis research on upper limb gesture classification [7, 11, 20, 29]. The arm positions were also picked based on these criteria, but also because changing the arm position changes each sensor modality's response to muscle pattern activation, so by collecting signal data in these arm positions, the system would capture the sensory patterns associated with arm position as well [11, 113].

The order of the hand/wrist gesture and arm position combinations were chosen at random and displayed on the monitor to instruct the participant, as indicated in Figure 3.9. Random combinations were chosen to remove the variability of fatigue from the experiment. Participants were asked to perform the gesture at a moderate and repeatable force level. The graphical user interface (GUI) prompted participants to hold each gesture/arm position combination for 3 seconds, while FMG, sEMG and IMU data were simultaneously collected. An average of the five FMG and sEMG sensor values was displayed for the participant during this time to provide them with visual feedback — something deemed critical by Lunardini et al. [38]. An example of how visual feedback was displayed to the subject can be seen in Figure 3.9(b). This was followed by a 3 second rest prompt in a neutral hand position during which sensor data were not collected, as seen in Figure 3.9(a). This was done for 10 repetitions, after which, the participants had a break until they prompted the investigator that they were ready for the next set of gesture/arm position repetitions to begin. In total, each participant performed 10 repetitions of every gesture/arm position combination, totalling 210 repetitions. The sensor data were timestamped, labelled with the gesture/arm position, and then saved for the offline processing discussed in the next chapter.



Figure 3.9: GUI displayed to participants while they are prompted to hold/release gestures. (a) shows the rest/neutral gesture screen with no live data recorded/displayed. The red indicator notifies the participant to release the gesture/rest. In (b) the participant is asked to hold the displayed arm position and gesture. The green indicator notifies the participant to hold the gesture/arm position and the live sensor data are displayed on the screen, with EMG and FMG data displayed in green and blue, respectively.



Figure 3.10: Hand/wrist gestures that were recorded: (a) wrist flexion, (b) wrist extension, (c) wrist pronation, (d) wrist supination, (e) hand closed (fist), (f) hand open, and (g) precision pinch.



Figure 3.11: Arm positions that were recorded: (a) low, (b) medium, and high arm positions.

Chapter 4

Data Processing and Pattern Recognition

The previous chapter outlined how FMG, sEMG and IMU data were collected while participants held important gestures for the ADL. The data were saved with a label of the gesture/arm position that was held during the data collection. Only static-gesture classification was explored for this work, so the transient gyroscope data were not used from the IMU. Only accelerometer data from the IMU was used for the gravity vector, as it pertains to arm orientation information. For the remainder of this thesis when referring to IMU data, it is only in regards to the x, y and z-axes accelerometer data, and sEMG will simply be referred to as EMG.

This chapter will describe the data processing procedure and subsequent use of the processed data with a pattern recognition algorithm to predict gesture labels — in other words, using sensory data collected at the forearm to interpret the intent of the participant. EMG, FMG and IMU data collected under each combination of gestures/arm positions were analyzed in Matlab. The process of signal filtering, segmenting, feature extraction, and data normalization will be referred to as data processing. After processing, pattern recognition was the process of training an ML algorithm with gesture labelled data, and then using the model to predict unlabelled data. Multiple myography modality combination data sets were made and assessed for this work. To interpret the results of the data processing and ML models, metrics such as classification accuracy and confusion matrices

were calculated for subsequent analysis in the following chapter.

4.1 Signal Filtering

EMG is a fairly weak signal with a low signal-to-noise ratio, so to be useful, the signal needed to undergo signal conditioning, or more specifically, filtering. The EMG hardware that was designed for this work had on-board amplification and filtering, but since the data were not digitized close to the measurement source, and the analog data were transmitted to the DAQ through a wire, there were sources of noise past the point of on-board filtering. For example, some artefacts were visible when the wire was moved or the subject fidgeted. It is likely that the wire acted as a receiver of electromagnetic radiation in the environment, although this was mitigated with the use of a shielded, multi-conductor cable from the multi-modal arm band to the DAQ. To assess the noise introduced by the wire, live data were displayed while the arm band was powered off and the wire was moved. There were several sources of interference identified. The greatest source of noticeable interference was isolated to the wire-to-DAQ interface and the arm band-towire interface. Interference of this nature is likely why filtering analog EMG data after it has been collected is widely accepted and used as EMG data processing best practices [11, 46]. Furthermore, filtering the analog data was critical when comparing the custom arm band designed for this work to other systems that had on-board ADC, since the systems that convert to a digital signal closer to the electrodes are more robust to noise [58].

To remove bias from the signal, a DC–DC filter is typically used on an EMG signal [11, 46]. For this work, a variable DC–DC filter was used. A variable DC–DC filter was applied to each EMG channel by calculating the mean of the first 500 samples (or 250 ms) of each repetition, and then subtracting the mean from the EMG signal value for every EMG signal value in that repetition. The DC–DC filter centred the EMG's amplitude about the x-axis, which has been found to make pattern recognition more reliable [59, 113]. The sample size was chosen because it aligned with the maximum 300 ms response time constraint needed for online applications.

The EMG circuit used for this work already had a 20–500 Hz bandpass filter, but it was visually noted during the experiment that there were EMG artefacts when the participant fidgeted

with their hands or feet. This was isolated, in part, to the wired connection of the analog system. Wired, analog systems are susceptible to motion artefacts, and ambient noise from electromagnetic radiation in the environment [58]. Thus, a 20–500 Hz 4th-order Butterworth bandpass filter was also applied to the data set to reduce this noise, as per EMG signal processing best practices [11, 46]. No notch filter was used to remove the power-line noise at 60 Hz because the information in this band also falls within EMG's dominant frequency range of 50–150 Hz [46, 58].

FMG sensors have a high signal-to-noise ratio and because the bumper FMG configuration was used for this experiment, the FMG system also benefited from some mechanical filtering [12, 64]. Thus, no filtering was applied to any of the FMG channels. The signal was acceptably decipherable without applying any filtering to the data set, as can be seen in Figure 4.1, and has shown repeated success without filtration in the literature [8, 64].



Figure 4.1: 5 channels of raw FMG data from the multi-modal arm band while the closed fist gesture is being held. Note the pressure signature change at the 0.75 s mark, which is when the participant responded to the GUI prompt and moved to hold the gesture.

The IMU's accelerometer sensor used for this work had a good signal-to-noise ratio, so no filtration of the x, y and z accelerometer data were used. Raw IMU data has also been used successfully in the literature, and looking at the data, it was clear that the changing gravity vector was decipherable between the three arm positions [12, 113]. An example of the differing IMU gravity vector for the three different arm positions can be seen in Figure 4.2.



Figure 4.2: IMU data plotted to show the effect of arm position changes on the accelerometer x, y and z-axes values. These values indicate how the gravity vector changes, relative to the positioning of the IMU on the participant's arm. The accelerometer data were plotted while in the (a) low arm position, (b) medium arm position, and (c) high arm position.

4.2 Signal Segmentation

The FMG signal was downsampled to 1000 Hz since this was the highest sample frequency found in the literature for pattern recognition using FMG [64]. 1000 Hz is on the highest end of what has been deemed necessary, but was used to remove sample rate as limiting factor of the success the experiment [8]. The IMU signal was only sampled at 140 Hz, and thus, as per previous work in the literature, the IMU data were upsampled using a cubic spline to 1000 Hz to match the sample rate of the FMG data [11].

The data set recorded for each repetition of gestures was collected for 3 seconds, but only the 1.5–2.5 second range was used for this work. This 1 second window segment was the most consistent across all participants. Before the 1.5 second mark, participants were delayed in reacting to the gesture prompt, and after the 2.5 second mark, during some repetitions, participants released the gesture early. Using the 1.5–2.5 second range removed these transient effects from the data set, simplifying the classification problem to static gesture classification. An example of the useful EMG data from the 1.5–2.5 s time segment can be seen in Figure 4.3. The data set was parsed from 3 seconds to 1 second of data, per 10 repetitions, of each of the 21 arm position/gesture combinations, for each of the 5 co-located FMG and EMG sensors, and single IMU, per subject.

State-of-the-art pattern recognition methods for prosthetic control systems require the use of feature-based data sets, which require the data to be segmented into appropriate window lengths [43]. In work by Englehart et al. [18], it is asserted that for real-time control, the system delay must be less than 300 ms. Although the analysis for this work was conducted offline, a window size that could accommodate the real-time threshold was chosen to simulate real-time conditions as per other previous work [11, 46]. Deciding a window length for three modalities was challenging since there have been no extensive studies to determine which window size is best for FMG signal processing [8]. For EMG, it was found that window length is proportional to classification accuracy, which comes at the cost of greater controller delays [46]. Overlapping windows refers to capturing part of the data from previous windows into the next, and allows for even less time delay between each window. A window length of 250 ms with an overlap of 50% (125 ms) was used since it is below the 300 ms constraint, and would allow for sufficiently quick response times. This window



Figure 4.3: Sample data set showing a participant's EMG while they are performing the closed fist gesture. The first column contains the EMG signals of Channels 1, 3 and 5; the second column contains the EMG signals of Channels 2 and 4. The red box indicates the time section that was parsed for static-gesture prediction.

length and overlap is also widely accepted in the EMG myocontrol literature [11, 46, 74]. These window characteristics were used on the signals of all three modalities since the criteria for FMG and IMU are not well established, and because it was imperative that each modality had the same number of samples per unit time to not bias the pattern recognition algorithm [11]. In Figure 4.4, it can be seen that each second of sampled data, which consists of 1000–2000 samples per sensor, is segmented into 7 sample windows. Features will be calculated for each window, and gestures predicted for each window.

4.3 Feature Extraction

Feature extraction is important for myocontrol because it makes pattern recognition algorithms more capable of deciphering patterns in complex input signals [46]. To accommodate real-time



Figure 4.4: One channel of FMG, EMG and IMU data is plotted to show how each modality's signal was segmented in the same way. From the 1 second of data per repetition, 7 window segments are created and used for subsequent feature calculation.

conditions, only features that could be applied online were considered. Also, only time-domain features were considered for this work because they are the most computationally-inexpensive features, and the most often used for real-time myocontrol applications. The features used for EMG were AR, MAV, WL and ZC. These features have been used successfully for EMG gesture classification by several groups in the literature, and are the ones most often used for interpreting gesture input from the upper limb [11, 59, 105]. To accommodate the use of window-based features and the requirement of the same number of samples per modality, a simple average of the signal over the time window, or MAV, was used for the FMG and IMU signals. The decision to use MAV for the FMG and IMU windows was further justified by its previous success in works on upper-body prosthesis control [8, 80].



Figure 4.5: Summary of the data set creation process that is done for each sensor channel.

4.3.1 Standardization

Pattern recognition algorithms can be imparted with false significance by the range and magnitude of the data used to train the algorithms, so it is critical that the data have a consistent scale [11, 46]. This is especially important when using features and data from various sensors, whose values are of varying scales. To reduce this discrepancy, each feature was normalized using the standard score equation, which is calculated as:

$$Z = \frac{X - \mu}{\sigma},\tag{4.1}$$

where X is the feature value, μ is the average of the feature set and σ is the standard deviation of the feature set.

By subtracting each independent feature value by the mean of that feature set, and then dividing that by the standard deviation of the set, each feature is left with a mean close to zero and standard deviation of 1. This step is also called auto-scaling, and is especially useful for FMG to mitigate the variability of the donning force of the arm band between subjects [8]. Standardization was used across all modalities and features.

4.4 Data Set Creation

To train the pattern recognition algorithm and test each modality combination, various data set combinations were created for this work. These are presented Figure 4.6. The modality feature data set was broken into modality pairs, which corresponded to modalities that have been tried in the literature, and they were FMG+IMU, FMG+EMG, and EMG+IMU. These data sets were also used to compare the performance of the custom system to previous work found in the literature. There were also two data sets created using the features from all three modalities. One of these sets was similar to the pair modality data sets, which included sensory data from all of the hand/wrist gestures, but another was made, called the main gesture set, that did not include the open hand and precision pinch hand gestures. Having a greater number of classes to differentiate between typically reduces the performance of a pattern recognition algorithm, so this set was created to test the system's performance when classifying fewer gestures. The five grasps chosen were deemed to be the most critical as they were the ones that were used in the literature the most often. These 5 data set combinations were created for each of the 23 subjects.



Figure 4.6: Visualization of how the modality combination data sets were organized and used to train the SVM classifier. Features from the respective modality are combined into one set and used to train one classifier; this is done for each subject.

Within each modality combination set, data from the participant's 10 repetitions of each ges-
ture/arm position were used. 8 repetitions were used to create a training set and 2 were used to create a testing set. To remove the variability of fatigue, the repetition number from each gesture/arm position set was randomized. The training set consisted of the processed sensor data, as well as the relevant classification labels, and was used to train the pattern recognition algorithm. Arm positions were not considered in the labels because gesture classification is the most important thing to predict for prosthetic control. Classifying gestures instead of arm position (or a combination of the two) is the most relevant for prosthetic control because users require that the control system is able to detect their gestural intent no matter the orientation of their arm. Detecting the intended arm position is not as critical, but is important to include that information so the pattern recognition algorithm that is tuned to each data set will learn how the gesture signal data looks in each arm orientation. For the testing set, the processed input data were configured in a similar way to the training set, except that it did not include the classification labels. The classification labels were kept separate so that after the tuned pattern recognition model used the test input data to make a prediction, the test set labels could be used to assess the accuracy and consistency of the model's predictions.

4.5 Pattern Recognition

After the data were processed, it was used as input data to train and test an ML, pattern recognition algorithm. Using pattern recognition algorithms for controlling prostheses is analogous to interpreting the intent of the user based on their processed biological signal data, and using that prediction to control a robotic prosthesis accordingly [43]. For this work, an SVM was chosen as the pattern recognition algorithm because of its efficiency and simplicity when compared to ANNs. LDAs, being the most computationally-efficient algorithm mentioned in Section 2.6 were also not chosen because SVMs are more customizable, making them highly tuneable and could be better optimized [82]. Another critical reason for choosing SVMs over other pattern recognition models was in consideration of future work. The intuitive next step from successfully classifying static gestural intent would be proportional control, which would require the use of regression pattern recognition modelling and prediction [4, 43]. With that in mind, SVM is very similar to the most popular regression model, SVR, which works on a similar working principle. The results of the SVM classification testing used for this work would be insightful for how the modalities would perform when using an SVR for regression prediction [8]. Testing the classification accuracy achievable by using the novel, multi-modal arm band designed for this work and comparing the modality combinations to ones previously tested in the literature will help to determine if the multi-modal arm band and using three modalities provides any benefits, and if so, could be used as the foundation for future regression prosthesis control works.

The Statistics and Machine Learning Toolbox in Matlab was used for its built-in SVM template. The template was used to train and tune an SVM model for each training data set input, which consisted of the modality combination's sensor features and gesture labels. Parameters and hyperparameters were optimized for each modality combination and subject-specific data set. The parameters and hyper-parameters tuned were the box constraints, kernel type, kernel degree, and gamma coefficient. An automated process that used a Bayesian search of parameters and hyperparameters was used to iteratively train and optimize an SVM for each data set. The optimization algorithm used was the sequential minimal optimization algorithm, and was used to find the best combination of parameters and hyper-parameters that yielded the highest accuracy and lowest validation loss. This optimized model was saved for subsequent use on the testing data set. The test data set was then used as input to the optimized model, and its gesture prediction outputs saved. These output results were compared to the known test set labels, and were used to calculate the classification algorithms' accuracy, recall and precision. The obtained performance metrics of the different modality combinations were used to assess and compare the system's performance, and will be discussed in the following chapter.

Chapter 5

Results and Discussion

To assess and compare the performance of the pattern recognition model for each modality combination, accuracy, precision, and recall were used to quantify their performance. Accuracy was calculated by dividing the number of correct class predictions by the total number of class predictions for that modality combination. Accuracy was also found for each sensing modality combination, per arm position (low, medium, high). These accuracy scores were averaged across all subjects. IBM SPSS 27 was used to conduct a statistical analysis for each of these scenarios to draw clear, statistically supported insights from the results.

To qualify the custom arm band designed for this work, benchmarks in the literature were used. Since the combination of FMG+EMG+IMU has not been used before with pattern recognition algorithms, the capabilities of the custom arm band had to be assessed by comparing modality pairs. For FMG+IMU, Menon and Sadarangani [30] tested a system with 3 FMG sensors and an accelerometer on 9 able-bodied subjects, and were able to achieve $92.67 \pm 7.86\%$ when classifying between grasp and release gestures. A follow-up study by Menon et al. [12] used 80 FMG sensors and an accelerometer on one amputee to get 99.8% classification accuracy on 6 gestures. The custom arm band developed for this thesis achieved $97.8 \pm 3.4\%$ across 23 subjects classifying 7 gestures. Although the FMG+IMU classification accuracy achieved by the system developed for this work was not as good as what was achieved by Menon et al., this thesis was tested on more than one subject. In the study by Menon and Sadarangani [30], which had 9 participants, there was large variability between participants, with some getting 100% and the worst getting 75.69%. This inconsistency is mirrored by the performance of the custom arm band and pattern recognition system developed for this work, which had 10 participants achieve 100% classification accuracy, while also having some of the worst performing classification accuracies across all modality combinations at 89.8%. For FMG+EMG, Jiang et al. [83] tested 5 able-bodied subjects using 8 FMG and 8 EMG sensors and achieved $91.6 \pm 3.5\%$ classification accuracy on 10 gestures. This is similar to the results achieved by the custom system developed for this work with $96.8 \pm 2.5\%$ across 7 gestures. The custom system designed for this work performed better percentage wise, but the comparison study had more gestures, putting it at a disadvantage — as the number of gestures increases, classification accuracy typically decreases because there are more patterns to distinguish between. For EMG+IMU, Englehart et al. [113] conducted a similar experiment to this thesis with 17 able-bodied subjects, 8 EMG sensors and an accelerometer to classify 8 gestures, and achieved accuracy of $95 \pm 1.7\%$, which is extremely close to the $95.6 \pm 3.2\%$ achieved by the custom system developed for this work. Overall, the results achieved by the custom multi-modal arm band developed for this work met the standards set by previous work that used modality pairs. Thus, the subsequent analysis and comparisons of modality pairs to three modality combinations can be made more definitively.

5.1 Overall Accuracy Results

For the overall accuracy comparison between sensor modality combinations, a one-way Within-Subjects Analysis of Variance (ANOVA) was used to analyze their overall performance. Pairwise comparisons with Bonferroni correction were also used. Normality was evaluated on the standardized residuals of these results using the Shapiro-Wilk test and it was found that four of the accuracy distributions were non-normal. Square, cube-root, and log transformations were used to potentially mitigate this issue, to no avail. This is likely because the data from most subjects were classified with an accuracy above 90%, forcing the distributions to skew to the left. To verify the results found by the parametric (ANOVA) testing, the non-parametric Friedman, and non-parametric pairwise tests were examined. The results of the parametric and non-parametric testing agreed with one another, so for simplicity, only the results of the ANOVA with Greenhouse-Geiser corrections were reported.

The difference between the classification accuracies of each modality combination was found to be statistically-significant (p <0.001), confirming the hypothesis that sensor modality has a strong influence on the accuracy of the SVM's ability to correctly classify gestures. The significance of this effect is strengthened by the fact that data was collected from sensors placed on the same location of the forearm, and during the same trials — mitigating the variance that could be introduced by sensors in slightly different locations and at different times. This distinction is important because these sensor modalities are affected by sensor location and subject physiology, which changes over time.

The observed power of this effect was 0.993, indicating that the relationship of modality to accuracy was almost perfectly captured by this experiment. Also, $\eta_p^2 = 0.348$, meaning that a moderate amount of the variance found in the experiment was due to the choice of modality combination. The observed power and η_p^2 were only given in the parametric testing and cannot be confirmed with non-parametric testing, and should be considered as having this limitation. Their values indicate that they successfully captured the modality effect, but that the variance of the results can be from many other things. Variance from factors other than modality makes sense in clinical trials, which have several varying factors. Many of the factors were controlled as much as possible — the same gestures, sensor location, allowance for rest between gestures, etc. — but there were still factors not captured or controlled by the experiment. This unaccounted for variance could be from subject physiology, or inconsistent arm band pressure and inconsistent rest intervals across trials.

Comparing the classification accuracy of the modality combinations, FMG+EMG+IMU had the highest accuracy $(97.9 \pm 1.9\%)$ when considering all of the gestures from the study. This was a statistically-significant improvement over EMG+IMU ($95.6 \pm 3.2\%$, p <0.001), and FMG+EMG ($96.8 \pm 2.5\%$, p <0.001), implying that using three modalities improves the ability of the pattern recognition to predict intent. FMG+EMG+IMU was not statistically different from using FMG+IMU ($97.8 \pm 3.4\%$), which is likely because the average classification accuracy is only 0.1% different, and this modality pair performed quite well. Of note, is that the standard deviation of FMG+IMU is much greater than FMG+EMG+IMU, implying that using all three sensing modalities is more consistent and can be attributed to the additional EMG feature information in the data set. The accuracy results are presented in Figure 5.1.



Figure 5.1: The mean classification accuracy of each modality combination. FMG+EMG+IMU (97.9 \pm 1.9%), FMG+IMU (97.8 \pm 3.4%), FMG+EMG (96.8 \pm 2.5%), EMG+IMU (95.6 \pm 3.2%), Main Gesture (99.2 \pm 1.3%). Error bars represent a 95% confidence interval. Note that the y-axis begins at 90%.

The worst case accuracies for the two best performing modality combinations (FMG+EMG+IMU and FMG+IMU) were 93.9% and 89.8%, respectively — showing that even at its worst, FMG+EMG+IMU performs well above 90%. FMG+IMU's worst case performance is nearly identical to the worst performing modality combination (EMG+IMU with 89.5%). This highlights FMG+IMUs ability to perform well, but also its inconsistency. Modality combination pairs with EMG included had lower accuracy, but also smaller standard deviations, which may imply that when EMG is incorporated, the system becomes more consistent, albeit is not as accurate as a system with FMG sensors.

Oddly, using FMG+IMU sensors presents no statistically-significant difference between any modality combination, even though its accuracy is so close to that of FMG+EMG+IMU, which

is significantly different than the other two modality combinations. This can either be attributed to its large standard deviation, with ten participants getting 100% accuracy and four having less than 92%, or the fact that it was the most non-normal result. This large discrepancy in accuracy results could be due to a lack of consistency in the donning pressure of the arm band, as it was wrapped around participants' forearms according to their comfort levels, and not force level, which the sensors are sensitive to. The signal was normalized to attempt to mitigate this issue; however, this effect is a known limitation of the current FMG sensing modality used for this work.

5.2 Arm Position Accuracy

For the accuracy comparison of each sensing modality per arm position, a three-way Within-Subjects ANOVA with Bonferroni correction and a pairwise comparison for the three arm positions was used. This was done to assess the robustness of each sensing modality to arm position effects. Assessing arm position accuracy is important for amputees in out-of-lab scenarios because for a prosthetic control system to be practical to use, it will need to perform in various arm positions when carrying out the ADL.

The combined effect of modality and arm position did not present significant differences. Looking at the pairwise analysis, it was also found that there was no significant difference within the same modalities between arm positions. As shown in Figure 5.2, the average FMG+IMU classification accuracy across the low, medium and high arm positions is very similar, but there is a large standard deviation. This implies that using this modality is robust to arm position, but suffers from inconsistencies between subjects. This could be from sensor limitations, or because of the lack of consistency in the donning pressure of the arm band — two of the known FMG limitations.

Using the FMG+EMG+IMU data set gave some of the highest accuracies across arm positions, with the smallest standard deviations, but interestingly it seemed, on average, to be more affected by arm position than FMG+IMU alone, although this effect was not significant. This could be attributed to noisy data introduced by the EMG data set. Modality pairs that included EMG had greater accuracy discrepancy across arm positions, which may be explained by the limb position effect and amount of contact between the EMG electrodes and the participant's skin in different



Figure 5.2: The mean classification accuracy of each modality calculated for the low, medium and high arm position, respectively. FMG+EMG+IMU (98.6 \pm 2.3%, 97.3 \pm 3.3%, 97.7 \pm 3.1%), FMG+IMU (97.5 \pm 4.6%, 97.9 \pm 4.0%, 98.1 \pm 3.6%), FMG+EMG (98.3 \pm 2.5%, 95.7 \pm 4.0%, 96.3 \pm 4.6%), EMG+IMU (96.4 \pm 3.4%, 95.7 \pm 3.8%, 94.8 \pm 5.6%). Error bars represent a 95% confidence interval. Note that the y-axis begins at 90%.

arm orientations. When the arm is in the medium and high position, electrodes on the top side of the arm band are pulled into the arm by gravity, while the electrodes on the opposite side of the arm band are pulled away from the forearm. This effect can cause electrodes to shift, and the level of conduction between the electrode and the skin to change, affecting the signal. This is not experienced by FMG+IMU because the limb position effect creates different pressure signatures on FMG sensors and is more decipherable, while EMG's limb position effect can limit the ability of EMG to detect MUAPs. The FMG+IMU data set had great average results, but again had large standard deviations across the arm positions, indicating inconsistent performance across trials. When all three sensors were combined, it had great accuracy across arm positions, but also added resilience and consistency to the system as the sensors are able to account for each other's limitations. This could be attributed to the classification model's access to ample information from the three modalities that could be parsed for recognizable patterns.

5.3 Classifier Performance

To properly assess the class predicting performance of the SVM models for each modality combination, confusion matrices were calculated for each modality. The confusion matrices and respective precision and recall scores can be found in Figure 5.3. Precision is an indicator of how much the model incorrectly predicts a class pattern to be that class, and recall is an indicator of how much each class recognized the class patterns associated with it. The precision and recall results for each modality are relatively balanced, indicating good model performance and that identifiable gesture and arm position patterns are being deciphered from the data. This helps to validate the methods chosen to collect and process the sensor data for this work [46, 59].

The misclassification values for FMG+EMG+IMU and FMG+IMU are much lower than those of EMG+IMU and EMG+FMG, which agrees with the ANOVA results mentioned previously. Looking deeper into how well each gesture was classified per modality, open hand and wrist supination are the most misclassified gestures across modality combinations that include EMG. It seems that when EMG data is considered, the model has a harder time distinguishing between gestures that share several muscle groups. Being able to distinguish between similar gestures is a known limitation of EMG, but is a strength of FMG — as seen by its lower misclassification rate. EMG+IMU, being the worst performing modality combination, is also limited by confusing gestures, but has confusion spread across nearly all of the gestures. When FMG data is considered, misclassification is not concentrated on a few gestures, but is spread out across several gestures and is another example of how FMG is affected by general inconsistency. For modality combinations including FMG, precision pinch was confused with gestures such as wrist extension, pronation, and flexion, and was spread out across these gestures.

With modalities that include EMG, misclassification between gestures is concentrated between gestures that activate similar muscles, while with FMG, the error is dispersed across many more of the gestures. This can be explained by EMGs limitation of detecting the MUAPs of adjacent muscles, which can confuse the pattern recognition algorithm. One of FMG's strengths is its ability



Figure 5.3: Confusion matrices, using the combined classification results for all subjects, for the (a) FMG+EMG+IMU, (b) FMG+IMU, (c) FMG+EMG, and (d) EMG+IMU modalities. Each matrix contains a positive/negative precision score summary in the final two rows, and a positive/negative recall score summary in the final two columns.

to distinguish between similar gestures so it is not affected by this, but is limited by inconsistency — which can be attributed to FMG sensor limitations and possibly inconsistent donning pressures across trials. Interestingly, for FMG+EMG+IMU, which includes both, error is low, but centred on misclassifying wrist supination with the open hand grasp, while evenly distributing and minimizing errors across the other gestures. This indicates that having FMG reduces misclassification between two gestures, by way of finding distinct patterns from similar gestures, and EMG helps reduce the overall, general error across multiple gestures — combining the benefits of both modalities, and showing a clear advantage in including all three sensing modalities.

The classification models using FMG+EMG+IMU data misclassified between open hand and wrist supination the most, and misclassification (precision and recall values) for the other gestures was low. If the open hand gesture was removed from the gesture pool, classification accuracy, recall and precision would get much better, and can be seen by the accuracy and low standard deviation of the main gesture data set which used FMG+EMG+IMU data, but only considered 5 gestures (99.2 \pm 1.3%). Results with better accuracy and consistency were expected with fewer, and more distinct gestures. The gestures chosen for the main gestures data set were the most critical for amputees, and had more distinct, measurable physiological patterns that made it easier for the model to differentiate. Thus, FMG+EMG+IMU could be made better immediately, and without losing functionality, by either using only the main gesture set, or by replacing the open hand gesture with one that is just as functional, but more physiologically differentiable from other gestures (such as relaxed hand).

5.4 Conclusion

In conclusion, the system designed for this work successfully met the benchmarks set by previous work that used pairs of modalities — and in many cases with fewer sensors. This proof of concept created a foundation from which to test the significance of introducing three modality combinations, and the benefits are relatively clear. Using three sensing modalities brought significantly better classification accuracy and consistency across the 23 able-bodied subjects who participated in the experiment. This improvement is likely attributed to the fact that having more modality types provides the pattern recognition algorithm with more phenomena to associate a pattern with. Each modality has limitations of what it is trying to measure and represent, so by having many different modalities that measure different phenomena, the modalities supplement for each other's limitations, allowing for the system to more comprehensively portray what is happening in the physical world, and the SVM is able to distinguish patterns from that data set, making the system more robust.

The benefits of multi-modal systems were discovered in previous works by using pairs of modalities, but this work took that idea a step further, and explored the benefits of adding a third modality. Interestingly, the modality combination pair of FMG+IMU also had great classification accuracy, albeit its results were less consistent. This modality combination was likely successful because capturing orientation effects with the use of an IMU helps to overcome a major FMG limitation — its susceptibility to the limb position effect and detecting pressure changes associated with things other than the volumetric changes caused by muscle contraction. Although FMG+EMG+IMU was the best performing modality combination overall, FMG+IMU showed similar accuracy results and would be both computationally and financially more economical. Going forward, it could be considered as an alternative modality combination with a similar balance between consistency/accuracy and cost.

Chapter 6

Concluding Remarks

6.1 Contributions

Multi-modal sensor and data fusion was deemed to be one of the leading ways to overcome the difficult task of giving amputees a natural feeling and intuitive way to control their advanced prostheses [4, 8, 64]. The objective of this thesis was to develop a system that explored sensor and data fusion to push the field of prosthetic control closer to a solution. To that end, this work investigated a combination of sensor and data fusion previously unexplored. The contributions of the work presented in this thesis were a novel, multi-modal arm band that integrated FMG, sEMG, and IMU sensors into a compact, wearable system that was used to collect muscle signal and arm orientation data from healthy subjects and amputees. This data-collecting device was used with custom software, GUI and experimental protocol that was designed to collect muscle signal and arm orientation information while subjects held gestures in arm positions that are critical for ADL. A large database of subject and sensory data was created from the experiment.

The database was used to conduct a proof of concept of the novel arm band by creating and using software that used literature-supported signal processing and pattern recognition techniques to test how gesture prediction compared to pre-existing technologies. The custom arm band created for this work met the benchmarks set by previous works. The custom arm band, data processing and pattern recognition software were then used to compare modality combinations, including one that was previously unexplored. A major contribution of this work was the statisticallysignificant improvement of using the unexplored modality combination, which was using all three sensing modalities — FMG, sEMG, and IMU sensors. This work used only 5 FMG and sEMG sensors, which was also fewer sensors than reported in previous work, meaning that this system performed similarly to previous work, but with fewer total sensors [4, 24]. These results helped to strengthen the argument of previous work, namely that multi-modal myography can improve the functionality of the prosthetic control system, while reducing the number of sensors required resulting in both cost and computational savings. The main benefits of combining FMG, EMG and IMU were that the system had more consistent classification performance across several gestures and arm positions, and the potential for cost savings by significantly reducing the number of sensors required for adequate performance. Some of the discovered downsides of such a system were the complexity of fusing the sensors and data of three separate modalities, which include more maintenance, data processing, and hardware design challenges.

From this work it was also found that an argument could be made for using just FMG+IMU without EMG. What limits advancement of this modality combination is the poor long term reliability of the popular FMG sensors chosen, which is likely why they have yet to be used for commercial systems. FMG+IMU did not perform as consistently as using three modalities, but there was no significant difference between FMG+IMU and FMG+EMG+IMU, meaning that FMG+IMU has the potential to adequately meet the minimum accuracy requirements for prosthetic control. FMG+IMU should be explored further as a cost-effective muti-modal fusion modality, since EMG sensors were the most expensive part of the system. It is possible that a system using only FMG+IMU sensors is adequately accurate, albeit less consistent, but this tradeoff may be acceptable to some end users — especially if it is at a much lower cost.

In summary, it was exhibited that the novel, multi-modal arm band met benchmarks set by previous work. No previous work fused these three sensing modalities with pattern recognition, ML technology, so the success of the arm band was assessed by comparing its performance to using modality pairs that have been tried before. It was found that the system created for this work was at least as good as those found in the literature, and with fewer sensors. This work contributes to the improvements of multi-modal control systems as a means to control mechatronic prostheses for amputees, and the thesis that providing more information to the control system with supplemental and redundant information from multiple modalities will result in a more accurate and consistent system.

6.2 Future Work

While the sensor and data fusion methods were successful at improving the performance of a prosthetic control system, the insights gained during this work indicate that a lot more could be done with the hardware, software and data set created.

A comprehensive data set of subject and muscle-signal data while holding hand/wrist gestures was collected while subjects moved from rest to the gestures of interest, but it was only used to classify static gestures. Gesture classification was an important step in giving amputees natural feeling control of their prostheses, but is limited in its applicability for out-of-lab use. The system did perform very well on the data set at static gesture classification — to the point that there was no need for extensive pattern recognition optimization to prove the modalities' efficacy — but when considering transient motions, or automating activity detection instead of manually parsing it (which are more realistic out-of-lab scenarios), the system accuracy would likely fall, as has been shown by Ferigo et al. [12]. At that point, the pattern recognition techniques would likely need to be optimized, or other, more advanced (possibly more computationally expensive) algorithms such as ANNs tried.

On the data processing side, experimenting with different features, and varying window sizes for FMG could also be done since only EMG had well-established signal processing processes to follow [8]. Using the existing data set, more advanced data fusion methods could also be explored, such as generating a gesture probability prediction using each modality, and then using those aggregate probabilities to make gesture predictions [46].

For this work, a separate pattern recognition model was made for each subject. Other work has tried the more difficult task of making the systems user-independent — meaning that they only train one pattern recognition model that can be used across a population, and is recommended this be tried with the existing data set. This makes the pattern recognition task more difficult because it must account for physiological differences, electrode placement differences, and movement pattern differences across subjects. For day-to-day applications of prosthesis control, user-independent classification could help reduce the calibration time required to use such a system, because data from previous users and calibration sessions could be used to train the ML algorithm [11]. Since differences in anatomy would likely cause deterioration in the model's ability to classify gestures, incorporating subject specific data such as sex, activity level and relative arm-fat values into the data set may also help the system account for the anatomical differences between participants [4, 24]. The recommendations of automating activity detection, including transient motions in the gesture recognition algorithm and user-independent models could be implemented on the existing data set created for this work, and could be used to further explore the arguments made for the modalities tested.

Large efforts were made to control for variability in the data set, but in hindsight, there were things that could have been done better. For example, controlled and consistent rest intervals may have been beneficial, since it was noted during the experiments that, although participants were given as much time as they needed to rest between sets — with the idea of removing fatigue as a variable — some participants chose to take minimal rest and may have pushed through even when fatigued. This could have affected the results, since it is known that fatigue affects both the EMG and FMG signals [4, 8]. Also, participants were asked to hold gestures at consistent and repeatable forces for the duration of the signal capture, but it was noted during the experiment that some participants were able to move to some of the gestures without much effort, while others needed to use more muscle activity to get there. This could be attributed to anatomical differences between subjects, but more specifically in this case, musculoskeletal anatomy, such as muscle tightness. This unconsidered variable likely introduced variability between subjects' FMG and EMG readings because these sensors detect muscle activity and not the gesture itself. If one person needed to use more muscle activation to achieve a gesture than another, their signals would have registered more clearly in the respective sensors' data, thereby affecting the pattern recognition algorithm's ability to decipher associated patterns.

To further reduce variability in the data set, a wireless device is recommended for future work, because the wire affected movement to and from certain gestures, and it was noted during experiments that subject jittering, and movement to and from intended gestures was a large source of artefacts in the EMG signal. EMG is known to be highly sensitive to sources of noise, and the wired connection also likely performed as an antenna which introduced more noise to the signals. Another limitation of the arm band designed for data collection was the choice of FSRs as the FMG sensor to use. FSRs are the most widely used FMG sensors, but have severe limitations in their out-of-lab application because they have large hysteresis, deteriorate over time, and their values depend highly on how tightly they are applied to a user. The FSR sensor limitations need to be addressed by either waiting for a more robust commercially available FSR, or attempt to implement TMG, which is a newer type of FMG that has been able to achieve promising results. Unfortunately, a system using TMG would need to be custom designed, and would be a large undertaking on its own. To mitigate the inconsistency of donning pressure, and to make the donning procedure more consistent, FSRs could be calibrated after each use and used to detect an arm band pressure threshold that notifies the investigator when the donning force is reached [8]. Even with these limitations, the performance of FMG+IMU was the second best performing modality. FMG+IMU has the potential to be a very affordable prosthetic control method. Although this modality combination was not as good as using the more complex, and expensive three modality combination, a strong argument can be made for FMG+IMU as a less consistent but significantly more affordable sensors for prosthetic control system. It is recommended that along with exploring FMG+EMG+IMU, FMG+IMU be investigated further, as a more cost-friendly, albeit less robust alternative.

The experiment conducted for this work was designed to be able to use the sensory data to classify static gestures. For a comprehensive prosthetic control system to be built, the system needs to work for amputees in out-of-lab scenarios, and thus needs to also give amputees the ability to control a prosthetic device in dynamic tasks and via proportional control. Having proportional control and the ability to predict classes during dynamic tasks are critical for an amputee to be able to perform important ADL tasks and task-oriented experiments. It is highly recommended that future work makes use of regression/proportional control models with the FMG+EMG+IMU and FMG+IMU modality combinations, in order to test the systems' efficacy, as regression and dynamic prediction usually perform worse than static classification [12]. SVM was chosen as the pattern recognition model for the work presented in this thesis because its regression, dynamic task predicting counterpart, SVR, has a similar working principle to SVM, and in theory, using SVM would give a relative indication of how the modality combinations would compare, and whether exploring FMG+EMG+IMU was worth the added complexity for future work [8]. There were significant improvements between modalities using SVM, and thus the regression model, SVR, should be used to predict force, gait, and dynamic tasks from data collected in an experiment focussed on this type of motion information [8]. The final test of such a system should be to assess the performance of the system on task-oriented experiments to test how the user performs with the system to complete actual ADL tasks, such as using the control system with a prosthetic limb to pick up a fork, fold a shirt, unscrew a bottle, or pin clothes to a drying rack [4].

Along with the challenging task of proportional control and testing the system to complete ADL tasks, it is imperative that future experimentation be done with amputees. Performance of the system with able-bodied participants gives some indication of how the modalities will perform, but amputees will be the end users of such a system so it is important to assess how an amputee would fair when using such a system [18, 35]. Ultimately, the goal of this work is to solve a problem that amputees face, and without testing potential solutions with amputees, the results are detached from the end user. The known limitations will affect the results, but there are also likely unforeseen nuances that will need to be addressed and considered as well [1]. There is a prevalent disconnect in the literature as 55% of upper limb prosthesis control research is conducted on subjects with intact forearms, while only 9% of papers in the last 20 years were conducted on transradial amputees [8]. Continuing to mostly experiment on healthy subjects is a disconnect from the target users who would benefit from a prosthesis control system and must be addressed for a working prosthetic control system to be considered a final solution.

References

- F. Cordella, A. L. Ciancio, R. Sacchetti, A. Davalli, A. G. Cutti, E. Guglielmelli, and L. Zollo, "Literature review on needs of upper limb prosthesis users," *Frontiers in Neuroscience*, vol. 10, pp. 1–14, May 2016.
- [2] A. D. Roche, B. Lakey, I. Mendez, I. Vujaklija, D. Farina, and O. C. Aszmann, "Clinical perspectives in upper limb prosthesis: an update," *Current Surgery Reports*, vol. 7, pp. 1–10, February 2019.
- [3] D. Yang, Y. Gu, N. V. Thakor, and H. Liu, "Improving the functionality, robustness, and adaptability of myoelectric control for dexterous motion restoration," *Experimental Brain Research*, vol. 237, pp. 291–311, February 2019.
- [4] M. Nowak, T. Eiband, and C. Castellini, "Multi-modal myocontrol: testing combined forceand electromyography," in 15th IEEE International Conference on Rehabilitation Robotics (ICORR), (London, England), pp. 1364–1368, July 2017.
- [5] E. A. Biddiss and T. T. Chau, "Upper limb prosthesis use and abandonment: a survey of the last 25 years," *Prosthetics and Orthotics International*, vol. 31, no. 3, pp. 236–257, 2007.
- [6] N. E. Walsh, G. Bosker, and D. S. Maria, *DeLisa's Physical Medicine and Rehabilitation: Principles and Practice.* London, England: Wolters Kluwer Health Adis, Fifth ed., 2012.
- [7] Y. Fang, N. Hettiarachchi, D. Zhou, and H. Liu, "Multi-modal sensing techniques for interfacing hand prostheses: a review," *IEEE Sensors Journal*, vol. 15, pp. 6065–6076, November 2015.
- [8] Z. G. Xiao and C. Menon, "A review of force myography research and development," Sensors, vol. 19, pp. 45–57, October 2019.
- [9] E. Cho, R. Chen, L.-K. Merhi, Z. Xiao, B. Pousett, and C. Menon, "Force myogrpahy to control robotic upper extremity prostheses: a feasibility study," *Frontiers in Bioengineering* and *Biotechnology*, vol. 4, pp. 1–12, March 2016.
- [10] G. K. Patel, J. M. Hahne, C. Castellini, D. Farina, and S. Dosen, "Context-dependent adaptation improves robustness of myoelectric control for upper-limb prostheses," *Journal* of Neural Engineering, vol. 14, pp. 1–15, October 2017.
- [11] J. G. C. Alfaro, "Implementation of user-independent hand gesture recognition classification models using IMU and EMG-based sensor fusion techniques," Master's thesis, The University of Western Ontario, London, Canada, 2019.

- [12] D. Ferigo, L. K. Merhi, B. Pousett, Z. G. Xiao, and C. Menon, "A case study of a forcemyography controlled bionic hand mitigating limb position effect," *Journal of Bionic Engineering*, vol. 14, pp. 692–705, October 2017.
- [13] E. R. Ramirez, "Control of a hand prosthesis using mixed electromyography and pressure sensing," Master's thesis, Polytechnic University of Catalonia, Barcelona, Spain, 2016.
- [14] J. Ghataurah, D. Ferigo, L.-K. Merhi, B. Pousett, and C. Menon, "A multi-sensor approach for biomimetic control of a robotic prosthetic hand," in *International Conference on Bioinformatics and Biomedical Engineering (IWBBIO)*, (Granada, Spain), pp. 74–84, April 2017.
- [15] T. Eiband, "Advanced myocontrol for hand and wrist prostheses," Master's thesis, Technical University of Munich, Munich, Germany, 2017.
- [16] M. Connan, E. R. Ramírez, B. Vodermayer, and C. Castellini, "Assessment of a wearable force and electromyography device and comparison of the related signals for myocontrol," *Frontiers in Neurorobotics*, vol. 10, pp. 1–13, November 2016.
- [17] N. Carbonaro, G. Anania, M. Bacchereti, G. Donati, L. Ferretti, G. Pellicci, G. Parrini, N. Vitetta, D. D. Rossi, and A. Tognetti, "An innovative multisensor controlled prosthetic hand," in XIII Mediterranean Conference on Medical and Biological Engineering Computing (MEDICON), (Seville, Spain), pp. 93–96, September 2013.
- [18] E. Scheme and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: state of the art and challenges for clinical use," *Journal of Rehabilitation Research and Development*, vol. 48, no. 6, pp. 643–659, 2011.
- [19] J. D. Lickley, The nervous system, an elementary handbook of the anatomy and physiology of the nervous system. London, England: Longmans, 1920.
- [20] N. Jiang, H. Rehbaum, I. Vujaklija, B. Graimann, and D. Farina, "Intuitive, online, simultaneous, and proportional myoelectric control over two degrees-of-freedom in upper limb amputees," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, pp. 501–510, May 2014.
- [21] M. McKinley, V. O'Loughlin, R. T. Harris, and E. P. O'Brien, *Human Anatomy*. New York, USA: McGraw-Hill Education, Third ed., 2012.
- [22] S. S. Fitt, Dance Kinesiology. Boston, USA: Schirmer, Cengage Learning, Second ed., 1996.
- [23] R. L. Linsheid, "Kinematic considerations of the wrist," Clinical Orthopaedics and Related Research, vol. 202, pp. 27–39, January 1986.
- [24] X. Jiang, L.-K. Merhi, Z. G. Xiao, and C. Menon, "Exploration of force myography and surface electromyography in hand gesture classification," *Medical Engineering and Physics*, vol. 41, pp. 63–73, 2017.
- [25] J. M. Kauer, "Functional anatomy of the wrist," *Clinical Orthopaedics and Related Research*, vol. 149, pp. 9–20, June 1980.

- [26] "Backyard brains," [online, cited July 2020]. Available from: https://backyardbrains. com/experiments/RobotHand.
- [27] Y. Kijima and S. F. Viegas, "Wrist anatomy and biomechanics," The Journal of Hand Surgery, vol. 34, pp. 1555–1563, October 2009.
- [28] A. Freivalds, iomechanics of the Upper Limbs: mechanics, Modeling and Musculoskeletal Injuries. Abingdon-on-Thames, Oxfordshire: Taylor and Francis Group, Second ed., 2011.
- [29] B. Peerdeman, D. Boere, H. Witteveen, R. H. in 't Veld, H. Hermens, S. Stramigioli, H. Rietman, P. Veltink, and S. Misra, "Myoelectric forearm prostheses: state of the art from a user-centered perspective," *Journal of Rehabilitation Research and Development*, vol. 48, no. 6, pp. 719–737, 2011.
- [30] G. Sadarangani and C. Menon, "A wearable sensor system for rehabilitation applications," in *IEEE 14th International Conference on Rehabilitation Robotics (ICORR)*, (Nanyang, Singapore), pp. 627–677, August 2015.
- [31] D. Yang, L. Jiang, Q. Huang, R. Liu, and H. Liu, "Experimental study of an EMG-controlled 5-DOF anthropomorphic prosthetic hand for motion restoration," *Journal of Intelligent and Robotic Systems*, vol. 76, pp. 427–441, 2014.
- [32] R. Braddom, *Physical Medicine and Rehabilitation*. Amsterdam, Netherlands: Saunders, Fourth ed., December 2010.
- [33] P. Maduri and H. Akhondi, Upper Limb Amputation. Treasure Island, USA: StatPearls Publishing, July 2020.
- [34] P. Montoya, K. Ritter, E. Huse, W. Larbig, C. Braun, S. Töpfner, W. Lutzenberger, W. Grodd, H. Flor, and N. Birbaumer, "The cortical somatotopic map and phantom phenomena in subjects with congenital limb atrophy and traumatic amputees with phantom limb pain," *European Journal of Neuroscience*, vol. 10, pp. 1095–1102, December 2001.
- [35] E. Campbell, A. Phinyomark, A. H. Al-Timemy, R. N. Khushaba, G. Petri, and E. Scheme, "Differences in EMG feature space between able-bodied and amputee subjects for myoelectric control," in 9th International IEEE/EMBS Conference on Neural Engineering, (San Francisco, USA), pp. 33–36, March 2019.
- [36] T. A. Kuiken, G. A. Dumanian, R. D. Lipschutz, L. A. Miller, and K. A. Stubblefield, "The use of targeted muscle reinnervation for improved myoelectric prosthesis control in a bilateral shoulder disarticulation amputee," *Prosthetics and Orthotics International*, vol. 28, no. 3, pp. 245–253, 2004.
- [37] S. N. Pierrie, R. G. Gaston, and B. J. Loeffler, "Current concepts in upper-extremity amputation," *The Journal of Hand Surgery*, vol. 43, no. 7, pp. 657–667, 2018.
- [38] F. Lunardini, C. Casellato, A. d'Avella, T. D. Sanger, and A. Pedrocchi, "Robustness and reliability of synergy-based myocontrol of a multiple degree of freedom robotic arm," *Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 9, pp. 940–950, 2016.

- [39] J. W. Sensinger and S. Dosen, "A review of sensory feedback in upper-limb prostheses from the perspective of human motor control," *Frontiers in Neuroscience*, vol. 14, no. 345, pp. 1– 24, 2020.
- [40] E. Scheme, K. Englehart, and B. Hudgins, "Selective classification for improved robustness of myoelectric control under nonideal conditions," *IEEE Transactions on Biomedical Engineering*, vol. 58, pp. 1698–1705, June 2011.
- [41] "Össur," [online, cited July 2020]. Available from: https://www.ossur.com/en-ca.
- [42] "Ottobock," [online, cited July 2021]. Available from: https://www.ottobock.ca/en/.
- [43] A. Fougner, O. Stavdahl, P. J. Kyberd, Y. G. Losier, and P. A. Parker, "Control of upper limb prosthesis: terminology and proportional myocontrol - a review," *IEEE Transactions* on Neural Systems and Rehabilitation Engineering, vol. 20, pp. 663–677, September 2012.
- [44] H. Basumatary and S. M. Hazarika, "State of the art in bionic hands," *IEEE Transactions on Human-Machine Systems*, vol. 50, pp. 116–130, February 2020.
- [45] F. Ryser, T. Butzer, J. P. Held, O. Lambercy, and R. Gassert, "Fully embedded myoelectric control for a wearable robotic hand orthosis," in 15th IEEE International Conference on Rehabilitation Robotics (ICORR), (London, England), pp. 615–621, July 2017.
- [46] J. Tryon and A. L. Trejos, "Classification of task weight during dynamic motion using EEG-EMG fusion," *IEEE Sensors Journal*, vol. 21, pp. 5012–5021, February 2020.
- [47] S. Wilson and R. Vaidyanathan, "Upper-limb prosthetic control using wearable multichannel mechanomyography," in *IEEE 15th International Conference on Rehabilitation Robotics* (*ICORR*), (London, England), pp. 1293–1298, July 2017.
- [48] A. Cloutier and J. Yang, "Design, control, and sensory feedback of externally powered hand prostheses: a literature review," *Critical Reviews in Biomedical Engineering*, vol. 41, no. 2, pp. 161–181, 2013.
- [49] Y. Xu, D. Zhang, Y. Wang, J. Feng, and W. Xu, "Two ways to improve myoelectric control for a transhumeral amputee after targeted muscle reinnervation: a case study," *Journal of NeuroEngineering and Rehabilitation*, vol. 15, no. 1, pp. 1–11, 2018.
- [50] I. Campanini, C. Disselhorst-Klug, W. Z. Rymer, and R. Merletti, "Surface EMG in clinical assessment and neurorehabilitation: barriers limiting its use," *Frontiers in Neurology*, vol. 11, pp. 1–22, 2020.
- [51] R. H. Chowdhury, M. B. I. Reaz, M. A. B. M. Ali, A. A. Bakar, K. Chellappan, and T. G. Chang, "Surface electromyography signal processing and classification techniques," *Sensors*, vol. 13, no. 9, pp. 12431–12466, 2013.
- [52] N. C. Arballo, D. M. Martínez, I. Soto, and B. Rodríguez-Tapia, "Myoelectric interfaces and related applications: current state of EMG signal processing–a systematic review," *IEEE Access*, vol. 8, pp. 7792–7805, 2020.

- [53] T. R. Farrell and R. F. Weir, "A comparison of the effects of electrode implantation and targeting on pattern classification accuracy for prosthesis control," *IEEE Transactions on Biomedical Engineering*, vol. 55, no. 9, pp. 2198–2211, 2008.
- [54] Y. Athavale and S. Krishnan, "Biosignal monitoring using wearables: observations and opportunities," *Biomedical Signal Processing and Control*, vol. 38, pp. 22–33, 2017.
- [55] "Coapt," [online, cited July 2021]. Available from: https://coaptengineering.com.
- [56] H. J. Hermens, B. Freriks, C. Disselhorst-Klug, and G. Rau, "Development of recommendations for sEMG sensors and sensor placement procedures," *Journal of Electromyography and Kinesiology*, vol. 10, no. 5, pp. 361–374, 2000.
- [57] A. S. Kundu, O. Mazumder, P. K. Lenka, and S. Bhaumik, "Hand gesture recognition based omnidirectional wheelchair control using IMU and EMG sensors," *Journal of Intelligent and Robotic Systems*, vol. 91, pp. 529–541, 2018.
- [58] J. Wang, L. Tang, and J. E. Bronlund, "Surface EMG signal amplification and filtering," International Journal of Computer Applications, vol. 82, no. 1, pp. 15–22, 2013.
- [59] J. Tryon and A. L. Trejos, "Performance evaluation of EEG/EMG fusion methods for motion classification," in *IEEE 16th International Conference on Rehabilitation Robotics (ICORR)*, (Toronto, Canada), pp. 971–976, June 2019.
- [60] M. Rojas-Martínez, M. A. Mañanas, and J. F. Alonso, "High-density surface EMG maps from upper-arm and forearm muscles," *Journal of NeuroEngineering and Rehabilitation*, vol. 9, no. 85, pp. 1–17, 2012.
- [61] Z. G. Xiao and C. Menon, "Performance of forearm FMG and sEMG for estimating elbow, forearm and wrist positions," *Journal of Bionic Engineering*, vol. 14, no. 2, pp. 284–295, 2017.
- [62] N. Thiamchoo and P. Phukpattaranont, "The study of EMG channel reduction for hand grasping classification," in 16th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), pp. 629–632, 2019.
- [63] S. Calinon, C. Castellini, M. Connan, and N. Jaquier, "Combining electromyography and tactile myography to improve hand and wrist activity detection in prostheses," *Technologies*, vol. 5, no. 64, pp. 1–16, 2017.
- [64] Z. G. Xiao and C. Menon, "An investigation on the sampling frequency of the upper-limb force myographic signals," *Sensors*, vol. 19, no. 11, pp. 1–18, 2019.
- [65] X. Li, Q. Zhuo, X. Zhang, O. W. Samuel, Z. Xia, X. Zhang, P. Fang, and P. Li, "FMGbased body motion registration using piezoelectret sensors," in 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), (Orlando, USA), pp. 4626–4629, 2016.

- [66] C. Castellini, R. Kõiva, C. Pasluosta, C. Viegas, and B. M. Eskofier, "Tactile myography: an off-line assessment of able-bodied subjects and one upper-limb amputee," *Technologies*, vol. 6, no. 38, pp. 1–15, 2018.
- [67] K. Weiss and H. Worn, "The working principle of resistive tactile sensor cells," in *IEEE International Conference on Mechatronics and Automation*, vol. 1, pp. 471–476, 2005.
- [68] "Interlink RPTF sensors," [online, cited July 2021]. Available from: https://www. interlinkelectronics.com/fsr-402.
- [69] D. Esposito, E. Andreozzi, A. Fratini, G. D. Gargiulo, S. Savino, V. Niola, and P. Bifulco, "A piezoresistive sensor to measure muscle contraction and mechanomyography," *Sensors*, vol. 18, no. 8, pp. 1–12, 2018.
- [70] D. J. Curcie, J. A. Flint, and W. Craelius, "Biomimetic finger control by filtering of distributed forelimb pressures," *IEEE Transactions on Neural Systems and Rehabilitation En*gineering, vol. 9, no. 1, pp. 69–75, 2001.
- [71] G. Lei, S. Zhang, Y. Fang, Y. Wang, and X. Zhang, "Investigation on the sampling frequency and channel number for force myography based hand gesture recognition," *Sensors*, vol. 21, no. 11, pp. 1–10, 2021.
- [72] C. Ahmadizadeh, B. Pousett, and C. Menon, "Investigation of channel selection for gesture classification for prosthesis control using force myography: a case study," *Frontiers in Bioengineering and Biotechnology*, vol. 7, no. 331, pp. 1–15, 2019.
- [73] T. Desplenter, Y. Zhou, B. P. Edmonds, M. Lidka, A. Goldman, and A. L. Trejos, "Rehabilitative and assistive wearable mechatronic upper-limb devices: a review," *Journal of Rehabilitation and Assistive Technologies Engineering*, vol. 7, pp. 1–26, 2020.
- [74] A. Radmand and E. S. K. Englehart, "High-density force myography: a possible alternative for upper-limb prosthetic control," *Journal of Rehabilitation Research and Development*, vol. 53, pp. 443–456, 2014.
- [75] C. Castellini, P. Artemiadis, M. Wininger, A. Ajoudani, M. Alimusaj, A. Bicchi, B. Caputo, W. Craelius, S. Dosen, K. Englehart, D. Farina, A. Gijsberts, S. B. Godfrey, L. Hargrove, M. Ison, T. Kuiken, M. Marković, P. M. Pilarski, R. Rupp, and E. Scheme, "Proceedings of the first workshop on peripheral machine interfaces: going beyond traditional surface electromyography," *Frontiers in Neurorobotics*, vol. 8, no. 22, pp. 1–17, 2014.
- [76] M. L. Delva and C. Menon, "FSR based force myography (FMG) stability throughout nonstationary upper extremity tasks," in *Future Technologies Conference (FTC)*, (Vancouver, British Columbia), pp. 891–896, 2017.
- [77] R. S. Chegani and C. Menon, "Regressing grasping using force myography: an exploratory study," *Biomedical Engineering Online*, vol. 17, no. 159, pp. 1–22, 2018.
- [78] M. Kok, J. D. Hol, and T. B. Schon, "Using inertial sensors for position and orientation estimation," Foundations and Trends in Signal Processing, vol. 11, no. 2, pp. 1–15, 2017.

- [79] V. Gregori, B. Caputo, and A. Gijsberts, "The difficulty of recognizing grasps from sEMG during activities of daily living," in 7th IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob), (Enshede, The Netherlands), pp. 583–588, August 2018.
- [80] A. Gijsberts, M. Atzori, C. Castellini, H. Müller, and B. Caputo, "Movement error rate for evaluation of machine learning methods for sEMG-based hand movement classification," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 4, pp. 735–744, 2014.
- [81] C. Castellini, R. M. Bongers, M. Nowak, and C. K. van der Sluis, "Upper-limb prosthetic myocontrol: two recommendations," *Frontiers in Neuroscience*, vol. 9, no. 496, pp. 1–4, 2016.
- [82] C. Ahmadizadeh, L. Merhi, B. Pousett, S. Sangha, and C. Menon, "Toward intuitive prosthetic control: solving common issues using force myography, surface electromyography, and pattern recognition in a pilot case study," *IEEE Robotics Automation Magazine*, vol. 24, no. 4, pp. 102–111, 2017.
- [83] S. Jiang, Q. Gao, H. Liu, and P. B.Shull, "A novel, co-located EMG-FMG-sensing wearable armband for hand gesture recognition," *Sensors and Actuators A: Physical*, vol. 301, pp. 1–5, 2020.
- [84] J. Sanford, R. Patterson, and D. O. Popa, "Concurrent surface electromyography and force myography classification during times of prosthetic socket shift and user fatigue," *Journal* of Rehabilitation and Assistive Technologies Engineering, vol. 4, pp. 1–13, 2017.
- [85] "Trigno," [online, cited May 2021]. Available from: https://delsys.com/trigno/.
- [86] U. Muhammad, K. Sipra, M. Waqas, and S. Tu., "Applications of Myo armband using EMG and IMU signals," in *IEEE 3rd International Conference on Mechatronics, Robotics and Automation (ICMRA)*, pp. 6–11, 2020.
- [87] A. Krasoulis, I. Kyranou, M. S. Erden, K. Nazarpour, and S. Vijayakumar, "Improved prosthetic hand control with concurrent use of myoelectric and inertial measurements," *Journal* of *NeuroEngineering and Rehabilitation*, vol. 14, no. 71, pp. 1–14, 2017.
- [88] D. G. K. Madusanka, L. N. S. Wijayasingha, R. A. R. C. Gopura, Y. W. R. Amarasinghe, and G. K. I. Mann, "A review on hybrid myoelectric control systems for upper limb prosthesis," in *Moratuwa Engineering Research Conference (MERCon)*, (Moratuwa, Sri Lanka), pp. 136– 141, 2015.
- [89] B. M. Booth, K. Mundnich, T. Feng, A. Nadarajan, T. H. Falk, J. L. Villatte, E. Ferrara, and S. Narayanan, "Multimodal human and environmental sensing for longitudinal behavioral studies in naturalistic settings: framework for sensor selection, deployment, and management," *Journal of Medical Internet Research*, vol. 21, no. 8, pp. 1–79, 2019.
- [90] D. Brunelli, A. M. Tadesse, B. Vodermayer, M. Nowak, and C. Castellini, "Low-cost wearable multichannel surface EMG acquisition for prosthetic hand control," in 6th International Workshop on Advances in Sensors and Interfaces (IWASI), pp. 94–99, 2015.

- [91] R. Merletti and S. Muceli, "Surface EMG detection in space and time: best practices," Journal of Electromyography and Kinesiology, vol. 49, pp. 1–16, 2019.
- [92] I. Elamvazuthi, Z. Zulkifli, Z. Ali, M. A. Khan, S. Parasuraman, M. Balaji, and M. Chandrasekaran, "Development of electromyography signal signature for forearm muscle," in *IEEE International Symposium on Robotics and Intelligent Sensors (IRIS)*, (Langkawi, Malaysia), pp. 229–234, 2015.
- [93] Y. Xiong and F. Quek, "Hand motion gesture frequency properties and multimodal discourse analysis," *International Journal of Computer Vision*, vol. 69, pp. 353–371, 2006.
- [94] A. Belyea, K. Englehart, and E. Scheme, "FMG versus EMG: a comparison of usability for real-time pattern recognition based control," *IEEE Transactions on Biomedical Engineering*, vol. 6, no. 11, pp. 3098–3104, 2019.
- [95] I. Kuzborskij, A. Gijsberts, and B. Caputo, "On the challenge of classifying 52 hand movements from surface electromyography," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, (Annual International Conference of the IEEE San Diego, USA), pp. 4932–4937, 2012.
- [96] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for EMG signal classification," *Expert Systems with Applications*, vol. 39, no. 8, pp. 7420–7431, 2012.
- [97] M. A. Oskoei and H. Hu, "Support vector machine-based classification scheme for myoelectric control applied to upper limb," *IEEE Transactions on Biomedical Engineering*, vol. 55, no. 8, pp. 1956–1965, 2008.
- [98] M. Totty and E. Wade, "Muscle activation and inertial motion data for non-invasive classification of activities of daily living," *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 5, pp. 1069–1076, 2017.
- [99] J. G. Colli-Alfaro, A. Ibrahim, and A. L. Trejos, "Design of user-independent hand gesture recognition using multilayer perceptron networks and sensor fusion techniques," in *IEEE 16th International Conference on Rehabilitation Robotics (ICORR)*, (Toronto, Canada), pp. 1103– 1108, 2019.
- [100] J. A. Lopez, "Motion intention estimation using sEMG-ACC sensor fusion," Master's thesis, The University of Western Ontario, London, Canada, 2021.
- [101] B. Crawford, K. Miller, P. Shenoy, and R. Rao, "Real-time classification of electromyographic signals for robotic control," *Proceedings of the National Conference on Artificial Intelligence*, vol. 2, pp. 523–528, 2005.
- [102] F. A. Omari, J. Hui, C. Mei, C. Mei, G. Liu, and G. Liu, "Pattern recognition of eight hand motions using feature extraction of forearm EMG signal," *Proceedings of the National Academy of Sciences, India Section A: Physical Sciences Volume*, vol. 84, pp. 473–480, 2014.
- [103] A. M. Martinez and A. C. Kak, "PCA versus LDA," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 23, no. 2, pp. 228–233, 2001.

- [104] Y. Geng, P. Zhou, and G. Li, "Toward attenuating the impact of arm positions on electromyography pattern-recognition based motion classification in transradial amputees," *Journal of NeuroEngineering and Rehabilitation*, vol. 9, no. 74, pp. 1–11, 2012.
- [105] Z. O. Khokhar, Z. G. Xiao, and C. Menon, "Surface EMG pattern recognition for real-time control of a wrist exoskeleton," *Biomedical Engineering Online*, vol. 9, no. 41, pp. 1–17, 2010.
- [106] K. Kiguchi and Y. Hayashi, "Motion estimation based on EMG and EEG signals to control wearable robots," in *IEEE International Conference on Systems, Man, and Cybernetics*, (Washington, USA), pp. 4213–4218, 2013.
- [107] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering*, vol. 50, no. 7, pp. 848–854, 2003.
- [108] Z. G. Xiao and C. Menon, "Counting grasping action using force myography: an exploratory study with healthy individuals," *JMIR Rehabilitation and Assistive Technologies*, vol. 4, no. 1, pp. 1–17, 2017.
- [109] Z. G. Xiao, Detecting upper extremity activity with force myography. PhD thesis, Simon Fraser University - School of Engineering Science, Burnaby, Canada, 2017.
- [110] K. Nolte, R. Merwe, C. Helena, H. Nolte, and J. Meulen, "A comparison between skinfold callipers and ultrasound imaging for assessing body composition in recreationally active students," *Ergonomics South Africa*, vol. 28, pp. 12–24, 2016.
- [111] J. Eckerson, J. Stout, T. Evetovich, T. Housh, G. Johnson, and N. Worrell, "Validity of selfassessment techniques for estimating percent fat in men and women," *Journal of Strength* and Conditioning Research, vol. 12, pp. 243–247, 1998.
- [112] N. Nazmi, M. A. Abdul Rahman, S. I. Yamamoto, and S. A. Ahmad, "Walking gait event detection based on electromyography signals using artificial neural network," *Biomedical Signal Processing and Control*, vol. 47, pp. 334–343, 2019.
- [113] A. Fougner, E. Scheme, A. D. Chan, K. Englehart, and O. Stavdahl, "Resolving the limb position effect in myoelectric pattern recognition," *IEEE Transactions on Neural Systems* and Rehabilitation Engineering, vol. 19, no. 6, pp. 644–651, 2011.

Appendix A

Permissions and Approvals

A.1 Ethics Approval



Date: 26 May 2020

To: Prof. Michael Naish

Project ID: 115674

Study Title: Multi-modal Sensor and Data Fusion using Machine Learning for Upper-body Prosthesis Control

Application Type: HSREB Initial Application

Review Type: Delegated

Full Board Reporting Date: 16June2020

Date Approval Issued: 26/May/2020 15:46

REB Approval Expiry Date: 26/May/2021

Dear Prof. Michael Naish

The Western University Health Science Research Ethics Board (HSREB) has reviewed and approved the above mentioned study as described in the WREM application form, as of the HSREB Initial Approval Date noted above. This research study is to be conducted by the investigator noted above. All other required institutional approvals must also be obtained prior to the conduct of the study.

Documents Approved:

Document Name	Document Type	Document Date	Document Version
Communication to Participant Scripts	Email Script	19/May/2020	1
Demographic Data Instrument	Other Data Collection Instruments	25/May/2020	1
Experimental Protocol	Protocol	19/May/2020	2
List of Instruments	Other Data Collection Instruments		
LOI & Consent	Written Consent/Assent	25/May/2020	3
Recruitment Poster	Recruitment Materials	14/May/2020	1

No deviations from, or changes to, the protocol or WREM application should be initiated without prior written approval of an appropriate amendment from Western HSREB, except when necessary to eliminate immediate hazard(s) to study participants or when the change(s) involves only administrative or logistical aspects of the trial.

REB members involved in the research project do not participate in the review, discussion or decision.

The Western University HSREB operates in compliance with, and is constituted in accordance with, the requirements of the TriCouncil Policy Statement: Ethical Conduct for Research Involving Humans (TCPS 2); the International Conference on Harmonisation Good Clinical Practice Consolidated Guideline (ICH GCP); Part C, Division 5 of the Food and Drug Regulations; Part 4 of the Natural Health Products Regulations; Part 3 of the Medical Devices Regulations and the provisions of the Ontario Personal Health Information Protection Act (PHIPA 2004) and its applicable regulations. The HSREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000940.

Please do not hesitate to contact us if you have any questions.

Sincerely

Nicola Geoghegan-Morphet, Ethics Officer on behalf of Dr. Joseph Gilbert, HSREB Chair

Note: This correspondence includes an electronic signature (validation and approval via an online system that is compliant with all regulations).

88

Jason S. Gharibo

Updated August 31, 2021

Education Western University M.E.Sc in Mechanical and Materials Engineering Supervisory Dr. Michel D. Neich	May 2019–Aug 2021
Supervisor: Dr. Michel D. Naish	
Western University	
Engineering Leadership and Innovation Certificate	Sep 2016–Aug 2018
B.S. in Applied Mathematical Methods B.E.S. in Mechanical and Materials Engineering	Sep 2015–Apr 2018 Sep 2011–Apr 2017
WE Go Global Certificate (International Exchange)	Sep 2011–Apr 2015
Masters Courses	
MME 9656 – Dynamical Systems Analysis	Fall 2020
MBP 9522 – Inferencing from Data Analysis	Winter 2020
• MME 9650 – Actuator Principles, Integration and Control	Fall 2019
• ECE 9603 – Data Analytics Foundations	Fall 2019
Honours and Scholarships	
Deans Honour List	2015
Publications	
Control of Twisted-coiled Actuators via Multi-DOF PID	
Parisa Daemi, Mena Kamel, Jason Gharibo, Michael D. Naish, Ana Luisa SPIE. Smart Structures and Nondestructive Evaluation, 2021.	Trejos, Aaron D. Price
Besearch Experience	
SAMS – Sensing and Mechatronics Laboratory Supervisor: Dr. Michel D. Naish	May 2019–Present
Teaching Experience	
• ES 3330 – New Venture Creation	Winter 2021
• MSE 2214 – Thermodynamics	Fall 2020
• ES 3331 – Managing Innovation and Design	Fall 2020
MSE 2202 – Introduction to Mechatronic Systems Design	Winter 2020