TASK-SPECIFIC VIRTUAL TRAINING FOR IMPROVED PATTERN RECOGNITION-BASED PROSTHESES CONTROL

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Abstract

The emergence of dexterous prostheses presents the potential to significantly improve amputees' quality of life. The use of intuitive pattern recognition algorithm is among the most promising control strategy for dexterous prostheses, with the demonstration of near perfect classification accuracies in laboratory settings. However, recent literatures show a weak correlation between classification accuracy and usability of the prostheses. External factors such as varying limb positions affect electromyography signals and consequently deteriorate usability of the prostheses; therefore, task-specific user training is proposed to enhance usability of the pattern recognition-based prostheses. Eight able-bodied subjects and one transradial amputee subject participated in the study to validate the efficacy of task-specific virtual training and examine the relationship between the virtual reality and real-world environment performance of prostheses use. Subjects were evaluated in 2 functional tests, Modified Box and Block Test and Reach-Grasp-Release Test, in both virtual and real-world environment, and received five sessions of one-on-one virtual training that lasted for one hour. Subjects were evaluated once again after completing five virtual training sessions and showed a significant improvement in functional tests. The amputee subject, despite the fact that he had been a pattern recognition-based prosthesis wearer for 5 months, also showed improvement upon virtual training, especially in the test that enforced him to use his prosthesis in postures that are outside of his usual range. In addition, no statistically significant difference was observed between the performance in virtual reality and real-world environment, indicating the potential for virtual reality evaluation to be a diagnostic tool to determine individual's usability of pattern recognition-based myoelectric prostheses. It was shown that high classification accuracy alone does not guarantee proficiency in prostheses control; rather, it only represented the capacity of one's prostheses control. To effectively prepare amputees for pattern recognition-based myoelectric prostheses control in activities of daily living, task-specific virtual training should be administered prior to prosthesis fitting. For future study, the integration of accurate, stable motion tracking system with head-mounted display is suggested for more immersive experience that enables users to practice proper positioning of the terminal device, an essential skill for object interaction with prostheses.

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Dedication

I would like to dedicate this thesis to my family.

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List of Abbreviations

ABP	Able-Bodied Prosthesis
ADL	Activities of Daily Living
AP	Action Potential
APL	Applied Physics Laboratory
ARAT	Action Research Arm Test
BMI	Brain-Machine Interface
CPRD	Committee on Prosthetics Research and Development
DARPA	Defense Advanced Research Projects Agency
DOF	Degrees-of-Freedom
ECoG	Electrocorticography
EEG	Electroencephalography
EMG	Electromyography
FDA	Food and Drug Administration
FES	Functional Electrical Stimulation
FMA	Fugl-Meyer Assessment
GUI	Graphical User Interface
IMU	Inertial Measurement Unit
JHFT	Jebsen-Taylor Hand Function Test
JHU	Johns Hopkins University

LDA	Linear Discriminant Analysis
LFP	Local Field Potential
MBBT	Modified Box and Block Test
MCT	Movement Completion Time
MPL	Modular Prosthetic Limb
MRMT	Move-Release Movement Time
MVC	Maximum Voluntary Contraction
PMA	Premotor Cortex
RGMT	Reach-Grasp Movement Time
RGRT	Reach-Grasp-Release Test
RW	Real-World Environment
SMA	Supplementary Motor Area
SR	Success Rate
TCS	Test Completion Speed
TCT	Test Completion Time
TD	Terminal Device
TMR	Targeted Muscle Reinnervation
UDP	User Datagram Protocol
VIE	Virtual Integration Environment
vMPL	Virtual Modular Prosthetic Limb
VR	Virtual Reality
VRE	Virtual Reality Environment
WMFT	Wolf Motor Function Test

Chapter 1: Upper Limb Motor Rehabilitation

1.1 Introduction to Motor System

Most routine activities performed in a person's everyday life comprises of motor functions, ranging from typing on a computer keyboard to drinking a glass of water. While these tasks seem trivial to execute, the inner workings of these motor functions involve a series of complex and precise collaborations between the central nervous system (CNS) that plans and generates motor commands and the peripheral nervous system (PNS) that executes these motor commands.

1.1.1 Mechanism of Motor Command

The primary motor cortex (M1), located in the frontal lobe of the brain, generates the neural impulses needed to propagate the signal for movement, with each hemisphere of the brain controlling the movement of the contralateral side of the body [1], [2]. The whole body is arranged somatotopically in the primary motor cortex, however, the amount of space taken up by a specific body part is dependent upon the complexity of the motor function [3]. For example, the dexterous movements of the hand would take up a much larger cortical space than the legs, which utilize more simple motor movements.

Other regions of the brain that control motor function constitute the secondary motor cortices, which include the premotor cortex (PMA), posterior parietal cortex, and supplementary motor area (SMA) [1]. The posterior parietal cortex functions to process multisensory cues into motor commands. This information is sent to the PMA, which controls spatial orientation and guidance-based movements, and to the SMA, which is involved in planning complex sequences of movements and coordinating bimanual movements [1].

The cortex projects to the spinal cord either directly through the corticospinal tract, or indirectly through the brainstem for motor outflow [2]. The brainstem, located in the posterior area of the brain, controls balance, posture, and head-neck coordination, whereas the spinal cord controls the motor outflow for control of voluntary body movements [2]. Signals traveling down the spinal tract synapse on interneurons and alpha motor neurons in the ventral horn of the spinal cord. These signals then innervate skeletal muscles and cause muscle contractions, which ultimately generate movement.

1.1.2 Mechanism of Muscle Contraction

Skeletal muscles act as the physical components that generate movement via contraction and relaxation. The cellular building blocks that make up skeletal muscles are muscle fibers, which are surrounded by an electrically excitable cell membrane called the sarcolemma [4]. The sarcolemma contains a network of conduits called the transverse tubules, which function as electrically excitable channels of extracellular fluid within the cells. The sarcolemma and transverse tubules contain voltage-gated sodium (Na+) channels and sodium/potassium (Na+/K+) pumps to maintain both a concentration and electrical gradient that helps to control and maintain membrane polarization [5]. Within muscle fibers are myofibrils, which are surrounded by the sarcoplasmic reticulum. The sarcoplasmic reticulum is a labyrinth of channels which function as a depot for calcium ions (Ca+) and is an integral component for facilitating muscle contractions. Muscle contractions are directly controlled by alpha motor neurons, which extends from the spinal cord and propagates a signal to downstream muscle fibers. The alpha motor neuron and all the muscle fibers that it innervates make up a single motor unit. A motor unit may contain anywhere from 3 to 1000 muscle fibers; the number of muscle fibers making up a given motor unit is generally proportional to the size of the alpha motor neuron axon [6]. A muscle typically contains multiple motor units called a motor neuronpool.

The signal generated from the alpha motor neuron that acts as the stimulus for muscle fiber contraction is called an action potential (AP). The AP induces the opening of voltage-gated sodium channels on the sarcolemma and causes an influx of Na+ leading to membrane depolarization [6]. The AP propagates bi-directionally allowing the subsequence segment of membrane to become depolarized. Depolarization of the membrane potential causes a release of Ca+ from the sarsmic reticulum into the myofibrils and triggers the myofibril to contract [2]. The magnitude of the contraction relies heavily on the number of motor units innervated and the frequency of the AP. Therefore, the summation of myofibril contractions dictates the strength of contraction and ultimately the degree of movement. Electromyography (EMG) recording enables to quantify this intensity of muscle contraction by measuring electrical voltage difference in two AP along the longitudinal axis of the muscle fiber [4], [6]. Generally, two differential electrodes are placed on the surface of the skin to detect the summation of all AP in the surrounding muscle fiber. As the AP propagates down a muscle fiber, the relative difference in surface voltages are measured to quantify the strength of muscle contraction.

1.1.3 Impairments Related to Motor Function

If the components that form the motor system could be related to a computer, the principal generation of neural impulses from the primary motor cortex of the central nervous system would be analogous to the software, or operating system of the computer. The skeletal muscles that contract and relax to move the body would be equivalent to the hardware constituents of the computer, for example, the keyboard or the mouse. Both software and hardware must work in concert for a computer to perform its function as intended. Without one or the other, the computer would cease to be a computer. To this end, there are impairments associated with motor function that affect different parts of the system.

A stroke, or a cerebrovascular insult (CVI), occurs when a blockage or leakage forms in an artery, depriving the brain of oxygen and nutrients. Impairment to motor control caused by the stroke-associated brain damage may be relative to a ‘software’ malfunction. While the ‘hardware’ is still intact, the areas of the brain controlling movement are often times unable to generate the neural impulses needed for movement or that these impulses are generated in a way that is erratic. Symptoms caused by stroke vary depending on the severity of the brain injury and may include motor impairments such as spasticity, weakness, muscle atrophy, and

Amputation of a limb is another type of impairment that affects motor function. It is the removal of a body extremity by trauma, prolonged constriction, or surgery [8]. An injury such as this may be relative to a 'hardware' malfunction. While the brain is not damaged, the amputated limb and the muscles that control movement of that limb are gone. Even so, the neural impulses that predicate the movement of the limb are still intact and the majority of the amputees may move their phantom limb by contracting muscles on the residual limb.

1.2 Motivation for Upper Limb Motor Rehabilitation

When one or more of the essential factors of motor control are damaged, one experiences functional limitation. Functional limitations are restrictions in performing fundamental physical and mental actions used in daily life due to impairments. Lower extremity functional limitations affect essential activities such as gait, mobility, and balance. In order to regain motor function and become independent, patients with lower extremity impairment seek appropriate therapy or assistive device. When upper extremity function is affected by impairments, especially in unilateral case, the rehabilitation is often abandoned early in favor of compensatory strategies. This decision is motivated by the decreased reimbursable patient-therapist contact time and the fact that the healthy limb with sufficient training can perform majority of activities of daily living (ADL) involving the upper limbs [9]. Nonetheless, this compensation not only is an inefficient way of motor control, but also results in learned non-use that hinders recovery of motor function in the impaired (affected) limb [10], [11]. In this section, the significance and shortcoming of current upper limb motor rehabilitation in two major fields are described.

1.2.1 Stroke Rehabilitation

Stroke is a leading cause of long-term disability [12]. Approximately 795,000 new or recurrent stroke occurs in the United States [12], and 49% of Americans have at least one of the three major risk factors of stroke; uncontrolled high cholesterol, uncontrolled hypertension, and smoking [13]. More than two-thirds of stroke survivors live with functional limitations and almost every patient that experiences stroke develops a physical disability that affects the activities of daily living (ADL) such as eating, dressing, and personal hygiene [14]. Hemiparesis, a weakness in one side of the body, is the most common cause of disability after stroke, affecting 70–85% of all stroke survivors [15]. It has been estimated that 60% of all surviving stroke patients may require rehabilitation treatment [16]. The direct and indirect costs of stroke in the U.S. for 2010 were $36.5 billion with an average expenditure of $5,455 per person [12].

Conventional stroke rehabilitation consists of physical and occupational therapy, and most of the stroke patients do not have access to receive the treatment beyond the verbal and physical guidance for repetitive movements. While conventional stroke rehabilitation should remain an important part of the therapy, there is a need for an additional therapy technique to overcome limitations of the current system. Conventional treatments rely on the use of physiotherapy that is partially based on theories and heavily dependent on training and past experience of the therapist. It has not yet been unveiled which method of therapy is more effective than the others in improving specific aspects of motor impairments [17], mainly due to lack of objective measures of patient's progress that can determine the effectiveness of therapy. Moreover, conventional treatments require labor-intensive one-on-one therapy. Research indicates that increasing the amount of training time helps improve motor function and can reduce long-term disability [18]–[22]. Despite this finding, it is economically impractical for patients to increase the number of hours with clinicians, given limited insurance coverage. Lastly, the repetitive nature of conventional treatments fails to maintain patients' motivation for continuous therapy. According to literature, patients' active involvement during the therapy is the key ingredient for the recovery of motor function [23], [24]. The conventional therapies often lack high motivational content and result in patients' abandoning many crucial rehabilitation exercises and tasks.

In order to address these key issues, the design of Smart Sleeve was initiated. Smart Sleeve is an activity monitor that can be worn throughout the day to monitor the affected limb usage and to provide visually engaging feedback to positively influence stroke patients' motivation, self-efficacy, and compliance. Unlike conventional therapy's repetitive exercises, Smart

Sleeve is built into daily life to encourage patients to learn efficient task-specific movement strategies in an everyday context by giving immediate, active, reward-based feedback about patients' progress and effort. Knowledge of an objective measure of the affected limb to healthy limb use ratio is expected to spark patients' motivation to improve on the previous day's ratio. With successful design and application, Smart Sleeve system will mitigate learned non-use and improve motor learning, while increasing patients' motivation to use their affected limb to the fullest possible extent. This active, engaging rehabilitation system has potential to transform patients' perspective in rehabilitation care from a sense of helplessness to a sense of empowerment. The detail description of upper limb stroke rehabilitation and Smart Sleeve design is on Appendix.

1.2.2 Amputee Rehabilitation

In the United States, an estimated 185,000 persons undergo a limb amputation each year, making approximately 1.6 million amputees living in the year 2005 [25]. Upper limb amputation is about 20 times less common than lower limb amputation, and the level of amputation varies greatly within this small population [26]. In one literature that summarized upper limb prostheses abandonment in the past 25 years, the average rate of abandonment for body-powered prostheses was 26% and externally powered prostheses was 23%, and many amputees addressed discomfort and lack of functionality as the main cause of abandonment

[27]. Even though issue of prosthesis discomfort must be addressed and resolved by technicians and engineers in the field, the prosthesis user also plays a significant role in reliable prosthesis control. One study reported that 90 percent of subjects who received rehabilitation training used their prosthesis functionally, while only 50 percent who did not receive rehabilitation training used their prosthesis functionally [28]. Research has shown that individuals fitted with a prosthesis within a “golden period” of 30 days benefit from a 93% rehabilitation success rate and a 100% return to work rate within 4 months of the injury [29]. Amputees who are fitted more than one month after surgery had a 42% rehabilitation success rate and a 15% return to work rate within 6 months to 2 years of time from injury to work [30]. By getting individuals engaged as early as possible in using their new prosthetic limbs, amputees are more likely to accept prosthesis and improve their quality of life [31].

However, there are limitations to early prosthesis fittings and amputee rehabilitation. First, medical reimbursement postpones the prosthesis fitting many months following an amputation surgery [29]. By the time amputees are fitted with a prosthesis, they have not only surpassed the “golden period,” but also become adapted to one-handed lifestyle that diminishes the need to use a prosthesis. Second, amputees do not gain enough experience with EMG-based interface prior to being considered a good or bad candidate for myoelectric prosthesis. Standard approach involves a simple myoelectric site testing to examine patient’s EMG signal activity and his/her potential to independently manipulate the residual muscles [32]. Once determined as a good candidate, the patient is fitted with a myoelectrtic prosthesis without further training. Third, amputee rehabilitation is rarely administered to upper limb amputees. A study indicates that less than 3% of upper limb amputees were discharged to a rehabilitation facility following amputation [25]. In addition, rehabilitation effort has been focused on proper fitting of the prosthesis, controlling phantom pain, and promoting wound care [32], but not on the control of myoelectric prosthesis. Fourth, rehabilitation for upper limb amputees is often only administered at large rehabilitation centers [25]. Most amputees cannot afford the costs and inconvenience of occupational therapy, limiting access to those living relatively close to those centers and financially stable. With a proper rehabilitation for myoelectric prosthesis control, amputees have potential to become a proficient and constant user of a prosthesis.

1.3 Thesis Overview

The main focus of this thesis project was to design and validate the use of task-specific virtual training in improved pattern recognition-based prostheses control. In Chapter 2, evolution of modern upper limb prostheses and control strategies are described. In Chapter 3, development of task-specific virtual training system and the study design to validate its significance on improved prostheses control are demonstrated. In Chapter 4, result of this study is illustrated and discussed. Chapter 5 concludes the thesis with design considerations for improved virtual training and future direction for upper limb prostheses. Finally, the proposal for a wearable activity monitor for stroke rehabilitation is described in the Appendix.

Chapter 2: Upper Limb Amputee Rehabilitation

2.1 Overview of Modern Upper Limb Prostheses

Upper limb amputations cause severe functional disability and have psychological implications [33]. Most upper limb amputations are acquired through traumatic injury, and sixty percent of traumatic amputation victims are active working adults between 21 to 60 years old [33], [34]. Traumatic injuries that require amputations typically result from accidents and violence, as is the case for war injuries, while tumors and other medical conditions account for most other upper limb amputations [35]. More than half of the major upper limb amputations cut through the radius and ulna (e.g., below elbow or transradial amputation) [34], but even with state-of-the-art prostheses, amputees experience difficulty returning to work and usually face a need to change vocational positions due to functional limitations [36]. Despite the success of lower limb prostheses as shown by 2012 Olympics runner Oscar Pistorius, upper limb amputees express a twenty to sixty percent rejection rate and high dissatisfaction regardless of the types of prostheses [37]–[41]. Upper limb amputees rarely use assistive devices at home, and often decide that it is better to live their lives without a replacement arm [27]. According to recent studies, the state of available technologies was a highly censured factor in this abandonment, specifically in the area of comfort and function [42].

Since the Iraq/Afghanistan War, the United States government has increased its funding towards upper limb prosthetics field, in hopes of helping veterans who have experienced serious war injuries. The Defense Advanced Research Project Agency (DARPA) Revolutionizing Prosthetics program provided research grants upwards of 30 million to aid in the development of better upper limb prostheses [43], [44]. Despite this effort, noninvasive technology with a reliable and intuitive control strategy still remains elusive. In this section, the basic design components, a history, current approaches, and state-of-the-art technologies of modern upper limb prostheses are discussed.

2.1.1 Upper Limb Amputation and Prostheses

The rehabilitation of upper limb amputation starts at a preoperative phase, where body condition is assessed and surgical level is discussed, and continues through life-long prosthetic/functional/medical assessment and emotional support [34]. For transradial cases, surgeons pay special attention to salvage the maximum length of the residual limb in order to provide broader options for applicable prostheses types. The amputation surgery includes myoplastic closure of the limb, which brings the developed myofascial flaps over the end of the residual bone to provide a cylindrical contour of the limb [45]. This not only provides soft tissue padding over the bones and better fixation of the bony lever arm in the surrounding soft tissue, but also prevents the bell clapper effect during the use of prostheses [34]. After surgery, amputees wait until their wound has healed and the stump has shrunk before they are fitted with prostheses. Although there are many types of prostheses and designs to meet an individual's specific needs, activity level, or purpose of wear, all modern externally powered trasnradial prostheses comprise 3 major components: the terminal device, a wrist unit, and the socket and suspension.

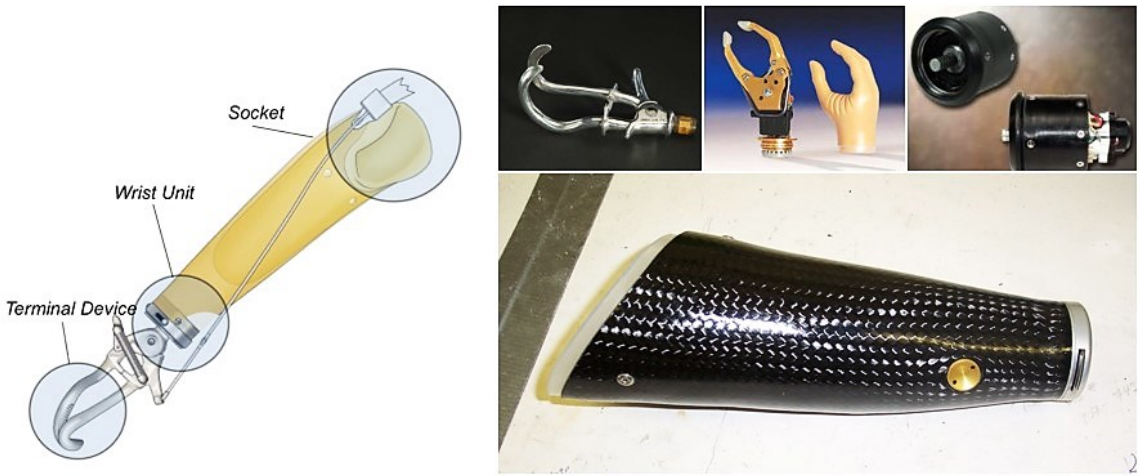

Figure 2.1: The picture above shows 3 basic components of modern transradial protheses: the terminal device (split hook or artificial hand), the wrist unit, and the socket. The split hook is the most popular terminal device, due to its durability, low cost, and easy maintenance. On the other hand, the artificial hand is cosmetically pleasing to fulfill social needs and the multiarticulated artificial hand offers more degrees-of-freedom than the hook's open/close function. The wrist unit is used to mimic forearm rotation, which provides functional benefit in object interaction. Some prostheses have flexion/extension and ulnar/radial deviation, however, the availability is limited to research facilities. The socket plays an important role in proper control of prostheses. The even distribution of pressure and secure electrode-skin contact is determined by the fit of socket.

2.1.1.1 Terminal Devices

The terminal device (TD) is situated at the most distal portion of the prostheses and is utilized as a substitute for the missing hand (Figure 2.1). Generally, either a split hook or a mechanical hand is used as the TD. Mechanical hand design ranges from simple one-degree-of-freedom (DOF) hands restricted to open/close movements to multiarticulated dexterous hands. For most externally powered single-DOF TD, one or two electromyography (EMG) electrodes are used to determine opening and closing of the hand. For multiarticulated TD, the handgrip patterns are pre-programmed and executed upon movement command. For example, Touch Bionics's i-limb™ ultra revolution (Livingston, United Kingdom) has 24 pre-programmed handgrip patterns along with 12 customizable handgrip patterns. Despite increased DOF, multi-DOF TDs are under-actuated, i.e. most of them still have 2-site control from forearm flexors and extensors. Some mechanical TDs have proportional control, and hence possess the ability to vary the speed and/or force of handgrip by supplying current that is directly proportion to the amputees' EMG signal strength. Although a mechanical hand is more aesthetic than a split hook, discomfort from additional component weight, expensive cost, and its high maintenance nature are notable drawbacks. A split hook was first introduced by David Dorrance in 1912 and has been the most popular TD [46]. A hook is lightweight, allows handling of small objects, and provides better visual feedback than a mechanical hand [32]. It is important to acknowledge that with commercially available prostheses, amputees do not receive sensory feedback from the object of interest and have to rely solely on visual feedback. Unlike mechanical hands, thin-profile hooks minimally limit amputees' view therefore are favored when picking up small objects. The hook's simple mechanistic design also makes it cheaper, durable, and advantageous for vocational needs. Individuals with social-psychological needs and a yearning for societal conformity prefer a mechanical hand over the hook [47], while those actively working with heavy-lifting objects favor the hook. Much research effort is directed towards engineering terminal devices combining both aesthetics and functionality.

2.1.1.2 Wrist Units

Wrist motion is vital for optimal positioning of the human hand for prehension, and loss of this motion greatly reduces the functional range of the hand. Although earlier prostheses put little emphasis on a functional wrist, modern prostheses either have a functional wrist unit or are modular to allow the placement of a wrist unit [48]. The wrist unit works as an attachment site for the terminal device to the forearm via interlocking threads that enables pre-positioning of the terminal device (Figure 2.1). There are 2 major types of powered wrists: (1) the rotation type, and (2) the rotation-flexion type [49]. The rotation type is the most common type of a wrist unit, which provides pronation and supination of the terminal device along with adjustable friction settings. Unlike the physiological forearm that has approximately 62-degree pronation and 104-degree supination range [50], commercially available wrist rotators may continuously rotate without such restriction. Though it may appear unnatural, this discrepancy plays an important role in providing further options for the prostheses control strategies. The rotation-flexion type includes flexion/extension of the terminal device, as well as features of the rotation type. The rotation-flexion type of wrist unit provides additional functional benefit, especially for essential activities near midline of the body. However, commercially available prosthetic wrist units are still a poor substitute for physiologic human wrist and forearm. Currently marketed prosthetic wrist units are measured to have at most two degrees of freedom and are often limited to static positioning of the terminal device for flexion/extension [51], while the human wrist and forearm have radial/ulnar deviation as well as flexion/extension and pronation/supination. Thus, engineering of future prosthetic wrist units are focused on restoring fluidity with increased DOF. The state-of-the-art prosthesis that functions closest to human wrist is the DEKA Arm System, which has a wrist unit that compounds flexion with ulnar deviation and extension with radial deviation.

2.1.1.3 Socket and Suspension

The sockets provide a load-bearing function and hold necessary components of the prostheses [52]. The prosthetic socket joins the residual limb to the prosthesis and is usually custom-made for each patient according to the shape and condition of the residual limb for total contact and even distribution of pressure (Figure 2.1). Proper fit and good adhesion is especially important for myoelectric prostheses, as poor fit may cause electrode lift-off and motion artifact. Externally powered prosthesis sockets have self-suspending closure systems, which ensure correct positioning on the residual limb with little to minimal harness. There are three major socket interface options: hard interface, soft interface, and gel liner interface [53]. The hard socket has rigid interface made of a laminate. Hard sockets are durable and less expensive, however, they are not advised for amputees with sensitive skin or bony residual limbs. Soft interfaces have rigid outer frames and flexible inner liners made of thermoplastics or similar materials. With heat application, a prosthetist can modify the shape of an inner liner when a change in amputees' residual limb shape or volume is observed. Perspiration absorption is minimal thus hygiene is not a big problem for the soft interface, nonetheless, the longer fabrication period is required compared to the hard interface. The gel liner interface is composed of flexible materials such as urethane, silicone, or thermoplastic elastomer. The gel liner is a thin protective membrane that is rolled over the residual limb to act as a 'second skin' between the residual limb and hard shell of the socket [52]. The gel liner minimizes movement and shear friction while providing more cushioning for comfort, therefore is advantageous for amputees with skin grafts or adherent scar tissue areas. The biggest drawback of gel liner interfaces is a matter of hygiene, as the material of gel liners is more prone to absorb sweat and needs daily cleaning. Also, gel liners are more expensive and less durable than other types of interfaces. Future generations of the socket component are being engineered to consist of different flexible, innovative materials for maximum comfort, hygiene, and functionality with the least financial burden.

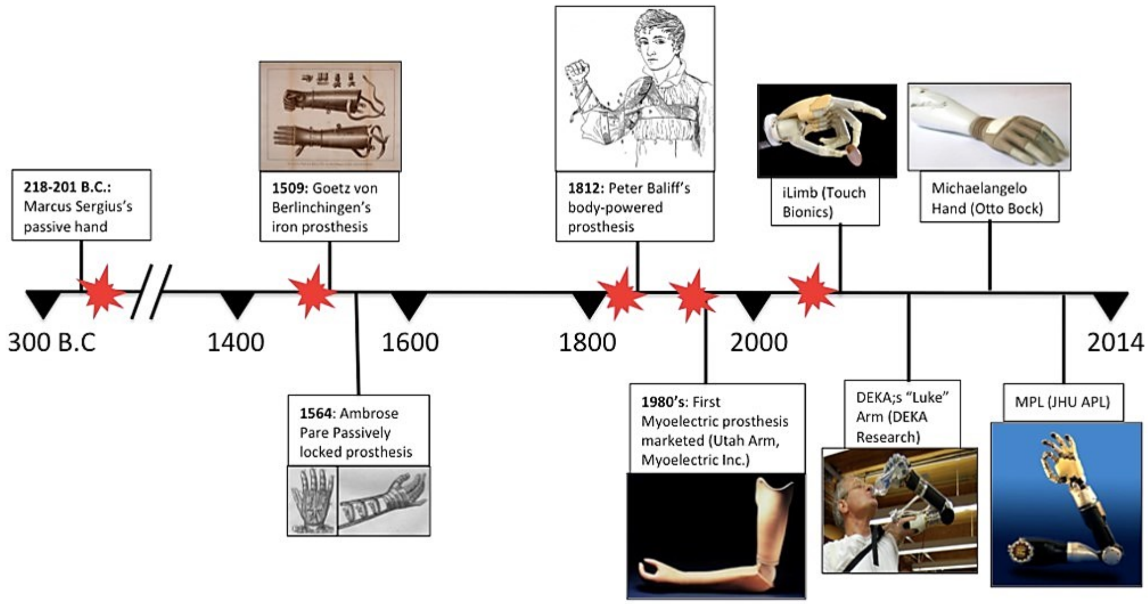

Figure 2.2: Timeline depicting major development in upper limb prostheses [54]–[57]. The red symbol indicates the occurrences of war. In 1800, the idea of using remaining body to operate the replacement limb was proposed and the mechanism behind body-powered prosthesis has made little change since then [58]. In early 1900, split hook was invented to allow amputees to grip or pinch objects and is still the most widely used terminal device in the market [46]. After World War II, many countries made attempts to develop more functional prosthesis for war veterans. 1982 marked the launch of first commercially available myoelectric prosthesis in America [57]. Upper limb prosthesis remained relatively unchanged until 2000's, when the multiarticulated prostheses were introduced and the government-funded projects have embarked the development of not only mechanically advanced, providing 26 degrees-of-freedom [59], but also neurally integratable prostheses. The future is headed for prostheses that can provide sensory feedback via direct interface with peripheral neurons.

2.1.2 History of Upper Limb Prostheses

The evolution of prostheses has a long history (Figure 2.2). The ancient Egyptians were said to be the early pioneers of prosthesis technologies. Their prosthesis was composed of fiber and used to create a sense of "wholeness" rather than for functional benefit [60].

CHAPTER 2. UPPER LIMB AMPUTEE REHABILITATION

Interestingly, noticeable development in the prosthetics field has always occurred before or after major wartime. Amputation has been performed from disease and traumatic injuries since thousands of years ago. However, due to poor wound care and high mortality rate of the procedure, the development of prostheses had little emphasis until the advent of anesthesia and advances in sterile in the 1840s. The most notable development was established by a Berlin surgical technician Peter Baliff during Napoleon War (1803-1815). He had an idea to move the prostheses with remaining power of the amputated limb and created the prosthesis by tightening tackles around elbow and shoulder [56]. In his design, elbow extension caused the thumb to stretch, and shoulder extension created the other fingers to stretch [61]. Adapting Baliff's concept of using remaining body as an actuator, William Selpho proposed "opening the artificial hand on one arm by a motion derived from the shoulder of the other arm of the wearer" [58] in 1857 and patented the first body-powered prosthesis. In 1912, David Dorrance revolutionized body-powered prosthesis with an introduction of a new terminal device, the split hook. His design is composed of a tweezers-like hook that is closed at rest and opened with shoulder movement [46]. Since then, underlying mechanism of modern body-powered prosthesis had little change. The first evidence of myoelectric controlled prosthesis is a patent filed in 1945 by German Physicist Reinhold Reiter. He introduced the idea of using amplified surface electromyography and converting it to motor control for operation of the prosthesis. However, his design was not portable, dedicated for factory workers, and lacked functionality and practically. Shortly World War II (1939-1945), rapid increase in research and development for better prostheses was sighted in multiple countries to encounter for injured war veterans. The United States also embarked its first government-funded prosthetics project and formed the Committee on Prosthetics Research and Development (CPRD) to develop more functional prostheses. In 1964, the Central Prosthetic Research Institute of the Union of Soviet Socialist Republics (e.g., Soviet Union) developed the world's first commercial myoelectric prosthesis [62]. In the United States, myoelectric elbow prosthesis, the Boston Arm [63], was developed in 1968, followed by 6-DOF enabled the Utah Arm in 1982 [57]. The Utah Arm, distributed by Motion Control (Salt Lake City, UT), used two electromyography (EMG) electrodes and applied a threshold-based control strategy to interpret muscle signals and converted them into motor controls, electrically powering one-DOF [56], [57]. Components of the Utah Arm included socket, 2 EMG electrodes, amplifier, battery, controller, and terminal devices and wrist [57]; these components are still used in state-of-the-art multiarticulated prostheses.

In the 21st Century, technological advances such as lighter motors, longer battery life, and development in signal decoding and control algorithms embarked a new generation of dexterous prostheses to become available. Touch Bionic's i-limb™ ultra revolution, RSLSteeper's bebionic3, Ottobock Healthcare's Michelangelo, DEKA Research's the DEKA Arm System, and Johns Hopkins University Applied Physics Lab's Modular Prosthetic Limb are all different variations of multiarticulated prostheses and they continually strive to pave the way for better, more functional prostheses that are comfortable and robust.

2.1.3 Review of Current Approaches for Transradial Amputees

There are different ways to adapt to a new lifestyle after amputation. It ranges from no cost of using no prosthesis to over $35,000 for the most advanced commercially available myoelectric prosthesis. In this section, the current approaches for transradial amputees are described and the benefits and shortcomings for each option are discussed.

2.1.3.1 No prosthesis

In average, one out of five amputees choose to not wear a prosthesis [27]. Although limited medical reimbursement, expensive cost, or phantom limb pain may contribute to this abandonment, discomfort from prosthesis wear and lack of functionality are the biggest factors amputees reject the use of prostheses in their life [42]. Amputees who choose this option will not have any financial obligation, however, there are several concerns regarding this decision. Amputees who adapt to one-handed lifestyle not only do not gain functional benefit in their Activities of Daily Living (ADL), but also endanger their safety and health.

One of the biggest drawbacks of wearing no prosthesis is an overuse syndrome. Overuse in amputees is similar to overuse of healthy limb in stroke patients; compensation of nonfunctional or lost limb is portrayed by the use of intact/healthy limb and other body part such as shoulder and mouth. Often times, overuse can be found in the form of repetitive strain-type injuries in which the person uses poor body posture of ergonomics to address certain tasks [64]. Also, wearing no prosthesis may result in uneven distribution of upper body weight, ultimately leading to spinal deviations. Moreover, spending a significant amount of time without prosthesis can imperil the amputees' potential for future prosthesis use, as muscle atrophy of residual limb impacts his/her ability to generate minimum signal strength required to become a myoelectric prostheses candidate. Therefore, amputees who decline a use of prostheses should be referred to an experienced occupational therapist, who can educate them on proper postures and ergonomics to preserve their health.

2.1.3.2 Passive Prosthesis

Passive prosthesis is a type of prosthesis that closely resembles the natural body part it is replacing, without having any powered moving parts (Figure 2.3). Since the first emergence of the passive hand in 300 B.C., the material has changed from iron to silicon and established a realistic appearance to fit the individual's unique needs. Amputees who choose passive prosthesis as their main option are seeking for aesthetic rather than functional benefit, and prefer its lightweight construction, minimal harnessing, and little maintenance [64]. Passive prosthesis costs are the lowest of all prostheses, ranging around $3,000. Even though it is

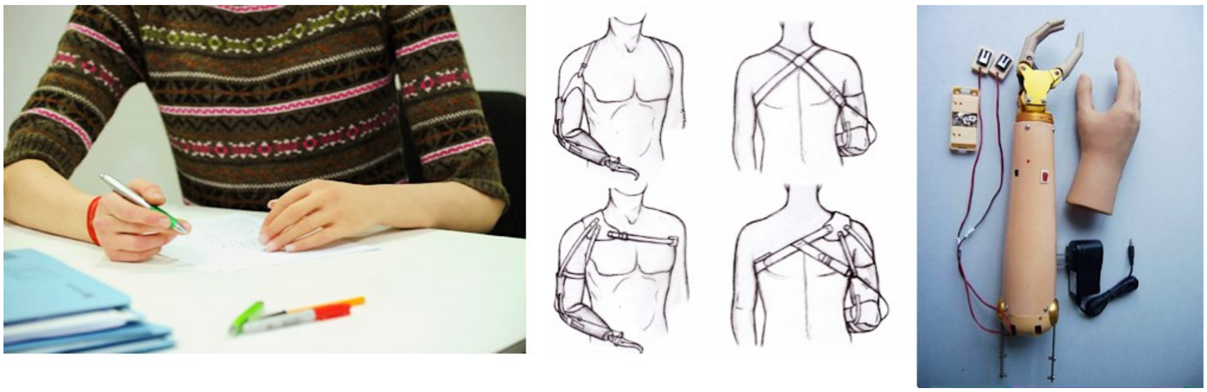

Figure 2.3: The type of prostheses is chosen based on individual's needs and financial constraints. The left panel shows an amputee using passive prosthesis to press down on the paper while writing. Passive prosthesis does not have functioning parts that can move, however, has realistic looking that can mimic hair, wrinkle, skin color, et cetera. The next panel shows the drawing of the body-powered prosthesis and its harness [41]. Body-powered prosthesis is most widely used upper limb prosthesis type for its reliability and low cost. The last panel shows the breakdown of myoelectric prosthesis. Electrodes placed on skin of amputees' residual limb detects signal upon muscle contraction, which is amplified and processed to command the motors to move. Myoelectric prostheses require battery, processing circuitry, and other electrical components, which increase the cost.

designed for purely cosmetic purposes, a passive prosthesis still provides basic functional abilities such as pushing, balancing, and supporting [65]. Some amputees purchase passive prosthesis as a secondary prosthesis directed for social events and alike, where life-like appearance of the lost limb is deemed influential during activities.

With the advancement of cosmetic skin in last decade, the role of passive prosthesis as an aesthetically pleasing alternative has decreased. With high-definition silicone elastomers that closely mimic human skin/hairs/fingernails, amputees are capable of using highly functional prostheses while pursuing the realistic look [66]. However, cosmetic glove needs to be replaced every three to six months, as it is prone to wear and tear with exposure to functional activities.

2.1.3.3 Body-Powered Prosthesis

Body-powered prosthesis is perhaps the most common type of prosthesis fitted within the United Sates. Body-powered prosthesis is composed of a harness/cable and terminal device that is attached to the socket via Bowden cable (Figure 2.3) [67]. The basic control mechanism has not changed for 200 years, but the harnessing has become more secure and efficient. Transradial body-powered prostheses use elbow flexion or biscapular abduction to activate the terminal device to open (voluntary opening design) or close (voluntary closing design) [68]. Voluntary opening design is the most commonly used type, in which the terminal device (TD) is closed at rest. The amputees use the cable/harness to open the device against the resistive force of rubber bands (for the hook) or springs (for the hand), then TD closes on its own with grip strength of installed rubber bands or springs. On the contrary, voluntary closing design refers to the type in which terminal device is open at rest. The force must be applied to close the TD, so the grip strength is limited by amputees' applied force. This design is heavier and less durable, but offers better control of closing pressure by providing feedback via cable tension.

Body-powered prosthesis provides lightweight construction, precision, as well as tension feedback from the cable at a low cost of $7,000. However, amputees face certain drawbacks such as uncomfortable harness, overuse injuries, and unnatural appearances [69]. The harness, which is essential not only for suspension but also for functionality, limits the range of motion and force output. Therefore, amputees are forced to use gross movement to activate the terminal device, consequently affecting proper function of intact limb and inducing faster fatigue. Study indicates that long-term use of body-powered prostheses can accelerate debilitating shoulder issues and anterior muscle imbalances and may lead to nerve entrapment within the contralateral axilla [70], [71]. Because of these shortcomings, many prosthetists nowadays recommend the myoelectric prostheses over the body-powered prostheses.

2.1.3.4 Externally powered prosthesis

Externally powered prosthesis is a relatively new type of prosthesis, first introduced to the market about 50 years ago. There are a variety of modalities available, e.g. touch pad, switch, force sensing; yet, the common terminology is associated with the myoelectric prosthesis. Myoelectric prosthesis is the most advanced and expensive type of commercially available prosthesis, ranging from $15,000 to $35,000 (Figure 2.3). The high cost of the device is due to additional components such as Electromyography (EMG) electrodes, signal amplifier, battery, and circuitry/controller [72]. Amputees generate EMG signals by contracting residual limb muscles, which are then converted into a form that can influence the electrical motors [73]. Since flexors and extensors of the residual limb are the most common sites of signal-thresholding [74] for transradial amputees, the device can operate independent of above-elbow movement. This is a big advantage compared to the control strategy of body-powered prosthesis, which pairs above-elbow movement with opening/closing of the terminal device. In addition, because the electrically controlled terminal devices contain motors, the gripping force varies by manufacturer and grip pattern, instead of user-applied force. According to the bebionc3 product brochure, the maximum grip force of power grip is 140.1 N, while that of tripod grip is 36.6 N [75].

The major limitation of myoelectric prosthesis is its increased weight from additional components, which can cause muscle fatigue or friction about the residual limb. Moreover, amputees' EMG control may not be as reliable as body-powered prosthesis, especially with multiarticulated terminal devices that require the control of multiple-DOF. Unlike mechanically operated body-powered prosthesis, myoelectric prosthesis demands more practice and is prone to misinterpret the user's intended movement.

2.2 State-of-the-Art Upper Limb Prostheses

Myoelectric prostheses have evolved most rapidly over the last decade. Depending on the cost and user's needs, myoelectric prostheses provide as little as single-DOF (conventional open/close) [76] or as many as 26-DOF terminal device (TD) [59].

2.2.1 SensorHand™ Speed and MC ProControl

Ottobock Healthcare (Duderstadt, Germany) is the world's largest and oldest prosthetics company. Company provides a wide range of prostheses, and one of the recent designs of single-DOF TD is called SensorHand™ Speed [76]. SensorHand™ Speed uses one or two EMG electrode sites to interpret use intentions with EMG thresholding method. SensorHand™ Speed provides fast response to EMG command, operating at speeds between 15 to 300mm/sec in proportion to the amplitude of muscle signals which is twice the speed of previous generations. Additionally, the AutoGrasp feature detects the object's slippage and increases the grip force to maintain the grip up to 100N [76]. This allows amputees to maintain the grasp with ease without consciously monitoring the force needed to prevent object from slipping, although this function may be turned off if amputees wish to have a full control of the prosthetic hand. Since SensorHand™ Speed is a single-DOF prosthesis, there is low susceptibility to a control failure and the price is lower than multiarticulated prosthesis. As a consequence, the system lacks dexterity and provides limited functional benefit.

After launching the Utah Arm, Motion Control (Salk Lake City, UT) has expanded their research to manufacturing a variety of modular parts that are compatible with popular prostheses models. The MC ProControl is a modular controller used for precise control of both hand and wrist [77]. Even though MC ProControl is not a terminal device, the development of this technology greatly impacted the prosthetics field. It not only presented easy calibration and re-adjusting of required strength of muscle signals (i.e. threshold), but also introduced co-contraction switching that allows the user to turn on the electric wrist by contracting two muscles at the same time [78]. Before the induction of MC ProControl, electric wrist rotation had to be turned on by pressing a switch with an intact limb or other body parts. The use of co-contraction enlightened other prosthetics companies to implement this control mechanism for a hands-free wrist switching. Even though it is a better alternative to pressing a switch, co-contraction control requires more training to perform and complicates the sequence of EMG commands.

2.2.2 i-limb and bebionic

i-limb and bebionic are the two most popular multiarticulated prostheses that provide handgrips other than open/close and move like a natural hand. Both prostheses originate from Europe; i-limb is manufactured by Touch Bionics (Livingston, United Kingdom) and bebionc is manufactured by RSLSteeper (Rochester, United Kingdom). Five independently controlled digits with individual motors and stall-detection circuitry allow the formation of dexterous grips [79]. Stall-detection circuitry detects when corresponding finger hits an object and stalls and allows the particular motor to stop, while the others continue to move to a desired grasp pattern [80]. Therefore, these hands can adapt to fit around the shape of the object to provide more secure grip than the SensorHand™ Speed. The main difference between two prostheses is that i-limb has a powered rotating thumb, while bebionic requires manual reposition of the thumb to switch between lateral and oppositional grip patterns.

Even though the most advanced version of i-limb, i-limb™ ultra revolution, has 36 grip patterns available (24 pre-programmed grips and 12 user-customized grips) [79], it can only provide five grip patterns at a time. Similarly, bebionc3's 14 grip patterns (Figure 2.4) cannot be accessed at the same time without reprogramming the hand [75]. This under-actuation is due to inherent restraint of threshold-based control. The control of the 2-site threshold-based mechanism is limited to 4 EMG signal commands: hold open, co-contraction, double impulse, and triple impulse. In order to access different grip patterns, amputees need to execute a command to switch to a desired grip patterns and then another command to close the hand in that configuration. In addition, to enter or exit from wrist movement, a separate command needs to be executed (Table 2.1). This complicated sequence requires tremendous amount of cognitive effort and often results in unreliable control. To overcome this limitation, Touch Bionics has developed a mobile application called "my i-limb", which allows users to change their prosthesis handgrip patterns with a simple tab of mobile device [81]. Another alternative input system is called grip chips™, which utilize Bluetooth technology for immediate access to a desired handgrip pattern. Although such systems have mitigated i-limb user's frustration, the fundamental problem of unnatural, cognitively overwhelming control has not been resolved. To unlock the full functionality and access any handgrips desired without conscious effort, these multi-articulated hands need a new control strategy.

Figure 2.4: Some of the grip patterns of bebionic3 [75]. Unlike lower-end myoelectric prosthesis that moves the hand as a whole, this multiarticulated terminal device allows for natural looking grasps. Unlike i-limb products, bebionic3 does not have motorized thumb and needs to be repositioned manually in order to access both lateral and oppositional grip patterns. One of the most useful features of multiarticulated prostheses is the mouse or keyboard grip, which eliminates the need for a stylus.

	Hand Open/Close	**Switch Handgrip Patterns**	**Wrist Control**
SensorSpeed™	Flex or extend	N/A	Co-contraction ➔ Flex or extend
i-limb™	Flex or extend	hold open, double impulse, triple impulse	Co-contraction ➔ Flex or extend
bebionic	Flex or extend	hold open, change thumb or press switch	Co-contraction ➔ Flex or extend

Table 2.1: The table shows commercially available terminal devices and their control strategies for myoelectric prostheses. Despite the number of DOF they should be capable of producing, multiarticulated prostheses are often underactuated due to limitation of threshold-based control. Unintuitive, complicated sequence of muscle contraction is required to access different handgrip patterns and wrist control.

2.2.3 Revolutionizing Prosthetics Program

Through Revolutionizing Prosthetics program solicited by Defense Advanced Research Projects Agency (DARPA) in 2006, many advances have been made in prosthetic limb and its control strategy. The goal of this project was to fund research organizations in the production of anthropomorphic prostheses that would most closely resemble a natural limb in look, feel, performance, and control. DARPA requested one organization to get an advanced prosthetic limb to the market quickly, and another to determine the feasibility of neoroprosthesis. Though both DEKA Arm System (Deka Research and Development Corporation, Manchester, NH) and Modular Prosthetic Limb (Johns Hopkins University Applied Physics Laboratory, Laurel, MD) are designed for transhumeral amputees, the modular design of these prostheses includes transradial amputees as user demographics.

Dean Kamen, inventor of Segway, took on DARPA's challenge with 18.1 million in funding and depicted success with the development of DEKA Arm System. DEKA Research and Development prototyped 18-DOF arm incorporating flexible socket design to ensure a secure fit to any amputees' stump modularly [98]. At only 8 lbs, DEKA Arm System contains electric motors, pressure control, and a vibrating device. Most amputees who are fitted with DEKA Arm System are transhumeral amputees who have undergone targeted muscle reinnervation (TMR) surgery and are capable of generating useful EMG signals. This surgical procedure involves rerouting of nerves of the lower arm muscles to higher regions of residual limb, in order to provide more distinguished EMG signal input for dexterous prosthesis control [82]. In addition to electrodes placed on the residual limb, a joystick-like controller installed in the shoe insole provides additional control [83]. Although less intuitive than upper limb muscle contraction, this foot-controller increases the number of DOF without creating confusion with other input sources [84]. Moreover, the vibrating device “tactor” provides haptic feedback based on the grip pressure, enabling finer control of prostheses. Initially, it was projected to cost about $100,000, which is a significant jump even from the most advanced multiarticulated prostheses on the market. Tom Doyon, Lead Electrical Engineer of DEKA Research and Development, announced in 2012 that a production-intent model was designed (Figure 2.5) [85]. In May 2014, United States Food and Drug Administration (FDA) approved DEKA Arm System with 510(k), and DEKA Research and Development team is currently pursuing to manufacture and commercialize DEKA Arm System to the market, hopefully with a smaller price tag.

Johns Hopkins University Applied Physics Laboratory (JHU APL) received the biggest funding with 30.4 million from DARPA for the project. In 2007, APL produced the Proto 1, capable of 8-DOF along with tactile feedback. In 2008, APL announced the Proto 2 of Modular Prosthetic Limb (MPL), acquiring 26-DOF and dexterity very close to that of a human arm, with flexible electrodes and a comfortable socket interface (Figure 2.5) [43]. The MPL

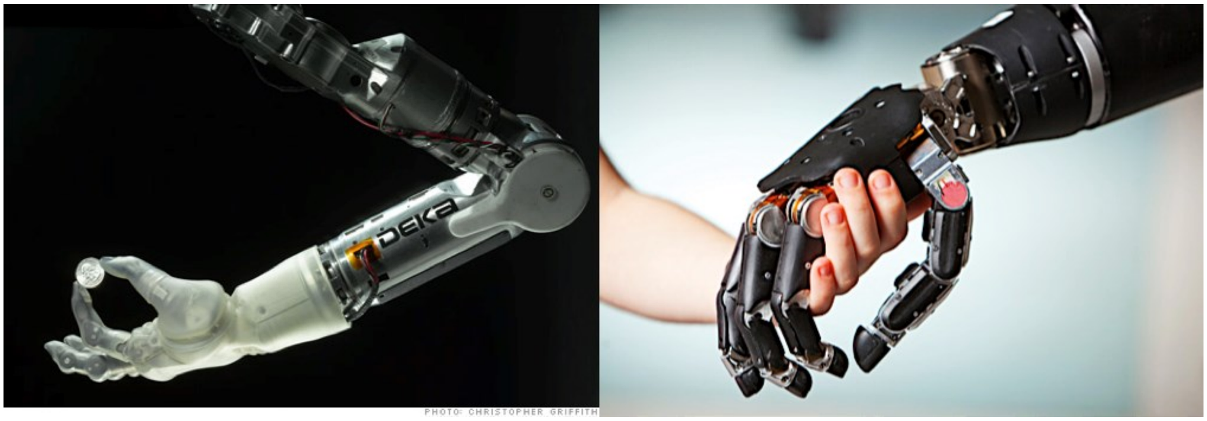

Figure 2.5: Major breakthrough in upper limb prosthetics field has been achieved through government-funded project, Revolutionizing Prosthetics. DEKA Arm System (shown on left) uses multiple inputs, such as foot control and myoelectric signal, to operate shoulder to fingers. The Modular Prosthetic Limb (shown on right) has 26-DOF and can be interfaced with simple myoelectric signal to electrocorticography signal, i.e “mind controlled”.

has anthropomorphic form factor and appearance, human-like strength and dexterity, and high-resolution tactile and position sensing. While mechanically feasible, amputees may have difficulty fully unlocking 26-DOF with surface EMG, as surface EMG does not provide resolution necessary to robustly operate 26-DOF [86]. MPL designed to work with a variety of human machine interface such as the conventional surface EMG interface, the implantable peripheral nerve interface, cortical implants (electrocorticography; ECoG), and the electroencephalography (EEG) interface [59], [87]. APL and supporting research teams have devoted their effort in developing and demonstrating neural implant devices as well as decoding algorithm. In 2011, teams led by APL have exhibited immense future of neuroprosthesis by having a tetraplegic patient successfully control MPL via ECoG. For future generations of this prosthesis, APL seeks to incorporate sensory feedback for touch, temperature, pressure, and vibration using cortical or peripheral nerve stimulation. APL established its pioneering role in future research of prostheses control/feedback with the development of MPL and its neural interface. With its cutting-edge and future forward solution, the MPL is said to cost more than $100,000, making it the most expensive and advanced prosthetic limb in the world.

2.2.4 Brain-Machine Interface in Research

Different types of input can be utilized in prostheses control. Besides body-powered prosthesis that mechanically translates gross physical movement to prosthesis functions, most of the externally powered prostheses require some sort of recording and processing of electrical signals from tissue or body parts. Although commercially available prostheses often use electromyography signals as input, there are other types of recording modalities in the research that provide direct communication between the brain and the prostheses, referred as brain-machine interface (BMI).

The recording that provides highest spatial resolution is a single-unit spike (< 500 μV, 0.1-7 kHz) [88]. Electrode microarrays are interested into brain and record the action potential directly from neurons. Due to high sampling rates needed to capture the features, single-unit spikes recording uses large multiprocessing demand-side platform, making a non-ideal solution for prosthesis control [89]. If the same approach is used to record lower frequency within a volume of tissue, the recording modality is called local field potential (LFP; <1 mV, <200 Hz) [88]. Lower frequency is less likely to be affected by geometry of electrode-tissue interface [89], making LFP a more favorable choice of BMI input. Despite high spatial and temporal resolution and potential demonstrated with non-human primates, spike trains or LFP are yet to be considered an ideal option for BMI. These invasive recording modalities need extensive research in enhancing the components and signal analysis, to be qualified for commercial use.

Often times, neuroprostheses research uses the recording modalities such as Electrocorticography (ECoG; 0.01-5 mV, < 100 Hz) or Electroencephalography (EEG; 5-300 μV, < 100 Hz). ECoG is a synchronized LFP measured by implanting microelectrodes on the exposed surface of the brain. Since recording is on the surface of the cortex, relatively fine spatial resolution and high signal-to-noise ratio can be obtained without the complications of single-unit spikes or LFP recording. The limitation of ECoG-based prosthesis is that ECoG recording requires invasive surgical procedure, craniotomy [90]. In September 2011, a volunteer with tetraplegia used ECoG to control prosthetic limb; first-ever accomplishment of ECoG-based prosthesis control by an individual with such disability. EEG is the summation of activities of millions of neurons with similar spatial resolution, measured by placing an array of electrodes along the scalp. Specifically, the magnitude of mu (8–12 Hz) and beta (18-25 Hz) rhythm over the sensorimotor cortex result in decreased amplitude when actual or imagined motor movements are performed [91], [92]. EEG recording does not require direct connection to peripheral nerves and muscles, thus its noninvasiveness has received much attention as a BCI for individuals with disability. However, the long distance between cortex and the recording site results in attenuation of action potential [89]. EEG has low signal-to-noise ratio caused by biological and ambient artifacts and less satisfying spatial resolution than ECoG. With its noninvasive nature and ability to provide greater resolution than recording modalities of commercially available prosthesis, EEG interface will continue to be at the frontier of neuroprosthesis. Research for the better signal decoding, analysis, and classification algorithms is ongoing to overcome problems implementing ECoG and EEG to large population.

2.3 Amputee Rehabilitation in Virtual Reality

Amputee rehabilitation is rarely occurring, and when it does, it usually represents the physical therapy relating to wound care. Amputees often consider their prosthesis a tool, rather than an extension of their body. If there is a knife that cannot cut properly, it will be stored in the bottom shelf of the kitchen or thrown into the trashcan. Similarly, if a prosthesis does not respond when amputees tried to open the door with it, the intact limb will be used instead to avoid being recognized as “different” in public. The cause of this unresponsiveness is most likely from user's improper control command rather than device malfunction. Nonetheless, repeated incidents like this cause amputees to lose trust in the function of prostheses and attribute to their abandonment of prostheses. Early adaption to a lifestyle with prosthesis is crucial in improving amputees' prosthesis control and lowering the abandonment rate.

2.3.1 Virtual Reality in Motor Rehabilitation

In recent years, the use of Virtual Reality (VR) gained its popularity in motor rehabilitation [93]–[98]. VR is computer-generated simulation of the real-world environment that is experienced by the user through a human-machine interface, primarily with a visual display. A fair amount of literatures state that people with disabilities can learn motor skills in a virtual environment and transfer that motor learning into the real-world environment [95], [99], [100]. There are three key concepts of motor rehabilitation that are easily applicable in VR rehabilitation: repetition, feedback, and motivation. Literatures have demonstrated that repetition is an important aspect of motor learning and rehabilitation [101], [102]. In reality, repetitive exercise requires a tremendous amount of time for medical personnel, which limits the population that can afford and benefit from this strategy. With the nature of computer-generated simulation, VR enables the user to have repetitive practice of isolated movements without the need for clinician's presence. Moreover, feedback, whether intrinsic of augmented, is proven to enhance motor learning [103], [104]. VR can simulate this behavior in real-time or score-related representations to reflect user's performance during task completion. Lastly, VR can make the rehabilitation process more engaging and fun for the user, increasing the motivation to endure practice [23], [24]. In addition to these 3 key concepts, VR is becoming a preferred method of motor rehabilitation, as it provides safe environment where patient can exercise despite the physiological limitation. The first use of VR in amputee rehabilitation was the simulation of mirror therapy to manage phantom limb pain [105], [106]. Soon after, few researchers have directed their attention to using VR as a training and evaluation tool prior to myoelectric prosthesis fitting [107]–[109]. The biggest challenge in early amputee rehabilitation for improved myoelectric control is the lack of feedback from residual limb. With VR, amputees can receive immediate, quantitative visual feedback in graphical interface such as bar graphs or virtual prosthesis, in response to user input (EMG signals). In this section, the use of VR in amputee rehabilitation is described.

2.3.2 MyoBoy® and virtu-limb™

MyoBoy® (Ottobock Healthcare, Duderstadt, Germany) is a real-time feedback system that is widely used during prosthesis fitting. The system is composed of MyoBoy® Hardware, MyoSoft® Software, two electrodes and electrode adapter, and cables. MyoBoy® Hardware has a 2-channel LED display, which visually presents the amplitude of EMG signals detected from electrodes. If an optional test adapter is attached to the hardware and one of the Ottobock

Healthcare's myoelectric prostheses, it is possible to control the tabletop prosthesis the same way in real-time. MyoSoft® has three main functions: measuring EMG signals, providing animated representation of virtual prosthesis, and allowing patients to play game for training purpose. Ability to measure and record EMG signals serves as an important evaluation tool. Prosthetist can systematically vary the placement and orientation of electrodes with visual feedback from MyoSoft® to determine the best placement of electrodes. Also, the analysis of EMG signal strength and amputees' ability to perform different movement commands provide prosthetist information regarding which type of myoelectric control suits the best for the individual. Moreover, having a graphical representation of EMG signal and its amplitude in reference to different myoelectric controls, MyoSoft® allows prosthetist to adjust gain of electrodes prior to obtaining and fitting the actual prosthesis to amputees. The second main function of MyoSoft® is controlling of virtual prosthesis. MyoSoft® is equipped with the full range of virtual Ottobock Healthcare's terminal devices and provides amputees a better understanding of how their EMG signal will affect different types of myoelectric prostheses and control mechanisms with the immediate response from selected virtual prosthesis. The third major component of MyoSoft® is a muscle training game interface. The game is controlled by activation and strength of the EMG signals and enables amputees to exercise and practice precise control of EMG movement commands in a jovial environment. However, given limited time amputees have with the prosthetist, majority of time is spent on first two functions of MyoSoft®. The record of patient evaluation from MyoBoy® as well as other factors such as amputees' needs and fiscal limitation play an important role in filling out a prosthesis prescription.

Virtu-limb™ (Touch Bionics, Livingston, United Kingdom) is a wireless simulation and training product for Touch Bionics myoelectric prosthesis. The system is composed of biosim software, electrodes and its adapters, the hardware, and the cable. Virtu-limb™ has all the basic functions that MyoBoy® offers, and has easier user interface. Virtu-limb™ has on-screen virtual representation of i-limb prosthesis that responses to different muscle commands, allowing i-limb candidate to experience and practice its multiple handgrip patterns. Similar to MyoBoy®, it's possible to connect virtu-limb™ system to the functional Touch Bionics myoelectric prosthesis. The main purpose of both MyoBoy® and virtu-limb™ are to expose amputees to myoelectric prosthesis control and to determine the best prosthesis device and control strategy for amputees. They are seldom used as a training device to improve amputees' myoelectric prosthesis control.

2.3.3 Research Prototypes

Few research teams have used virtual prosthesis to facilitate user training of multiarticulated prostheses. Two notable VR systems are the Virtual Reality Environment (VRE) designed for the Department of Veterans Affairs to optimize the DEKA Arm System and MyoTrain designed by previous master's student at the Johns Hopkins University

Biomedical Engineering Department to enhance the pattern recognition-based myoelectric prostheses control.

DEKA Arm System has multiple inputs to maximize the fluidity of control. The control options include foot controls with inertial measurement units, pneumatic bladders, manual switches, and myoelectric sensors [44]. Because DEKA Arm uses multiple inputs to create simultaneous, coordinated movement, control may not be as straightforward as flexing and extending forearm muscles like commercially available prostheses. In order to prepare amputees and determine efficacy of DEKA Arm System control in the real world, VRE was developed for the study in the Department of Veterans Affairs. The VRE consists of real-time 3-Dimensional avatar (Figure 2.6), which moves in a same manner DEKA Arm System does upon receiving input commands. Observing the real-time responses on the avatar, amputees can experience activating the motor pathways required to operate the DEKA Arm System [107]. The training was given in two stages; practicing gross movements then practicing complex sequential movements. In a case study of this VRE, an amputee was considered a competent user of DEKA Arm System who can perform functional and recreational activities upon 3 ½ hours of virtual training [107].

MyoTrain is an application of virtual modular prosthetic limb (vMPL) model designed by JHU APL during DARPA's Revolutionizing Prosthetics program. EMG pattern recognition algorithm has long been studied but there are only a few research facilities that have functional

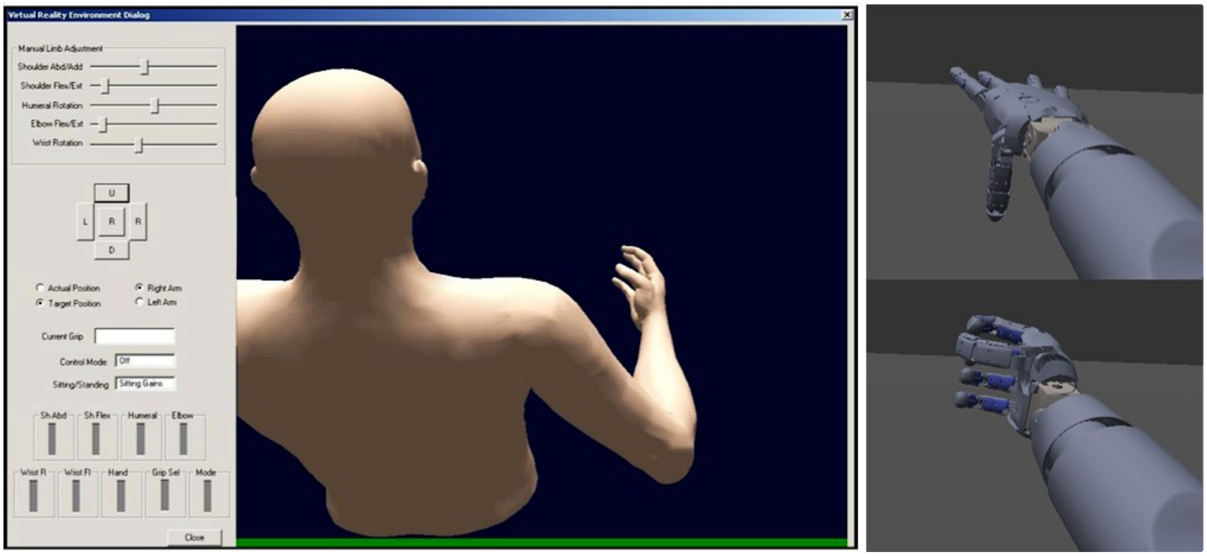

Figure 2.6: On the left is the immersive first-person view of the DEKA Arm System's VRE [107], which responds the same way physical DEKA Arm System would. A case study indicates that upon 3.5 hours of VRE training, an amputee was able to operate DEKA Arm System for functional activities. Another amputee rehabilitation training uses real-time decoded virtual prosthesis for pattern recognition-based control. The study indicates that the classification accuracy of all amputee participants significantly improved upon 10 sessions.

pattern recognition-based myoelectric prosthesis. There are various hurdles in bridging the gap between research and clinical setting, and development of MyoTrain strives to resolve one of the issues. MyoTrain is a training and evaluation tool for pattern recognition-based virtual myoelectric prosthesis. Upon calibration of pattern recognition classifier, amputees can practice reproducing EMG signal pattern with the visual feedback of virtual prosthesis (Figure 2.6). The virtual prosthesis moves according to the decoded movement commands, providing essential information to determine where the confusion and misclassification occurs. Immediate response of virtual prosthesis allows amputees to experience and memorize the

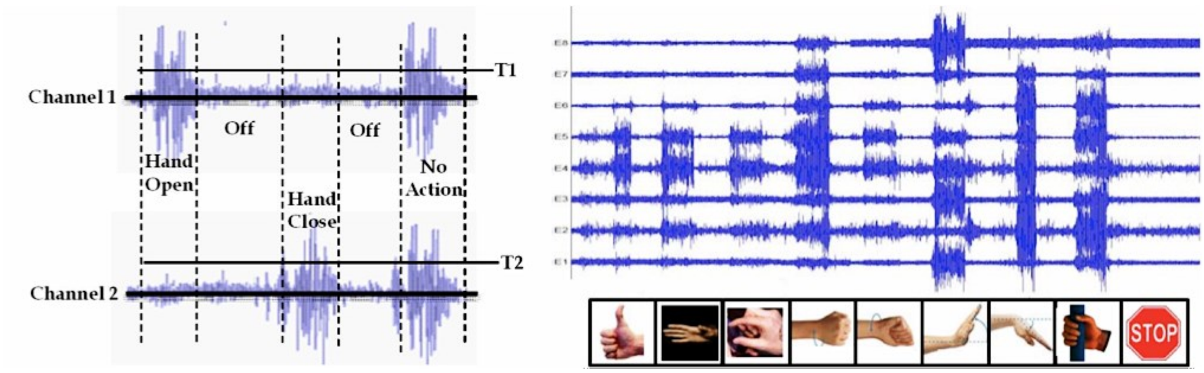

Figure 2.7: Two types of myoelectric control strategy are demonstrated. On the left, a two-channel thresdhold-based control for conventional 1-DOF myoelectric prosthesis is labeled [74]. Using this control strategy, proportional speed control can be obtained based on amplitude of EMG signals. The right panel shows a pattern recognition-based control. The signal patterns are used to classify different movement commands. The biggest benefit of pattern recognition-based control strategy is that it allows intuitive control.

degree of contraction, location of muscle contraction, and configuration of phantom limb when the desired movement is executed. This visual feedback positively reinforces amputees to stay motivated during rehabilitation. Upon 10-sessions of amputee rehabilitation with MyoTrain, all amputees significantly improved in their ability to control 9-movement class with virtual prosthesis ($n=4$, $p<0.01$) [109].

2.4 EMG Signal Processing

There are two broad categories of myoelectric control strategy: threshold-based control and pattern recognition-based control (Figure 2.7). Threshold-based control was first introduced over 50 years ago [110] and is still used in almost all myoelectric prostheses in the market. It is based on the comparison of the generated EMG signals to a fixed value, i.e. threshold, and functions much like a binary system. For conventional two-site myoelectric control, electrodes are placed over flexor and extensor on the forearm of transradial amputees and whether or not each site's EMG signal amplitude is above the fixed threshold determines different movement commands such as hold open, co-contraction, double impulse, and triple impulse which then gets decoded to movement commands. Using two-site threshold-based control for multiarticulated prostheses is cognitively overwhelming, as amputees must generate a series of unnatural muscle contractions with accurate amplitude, timing, and duration.

Researchers have found pattern recognition as a control strategy that can potentially resolve this problem [111], [112]. Pattern recognition control is assignment of a label (movement command) to a provided input (EMG signal pattern). First, the data is preprocessed and windowed to obtain meaningful segments. Second, features are extracted from the raw EMG signals in each segment. Third, a classifier compares these features to the labeled examples given during calibration and determines the most probably category of the current input. Then, a controller outputs movement command associated with the labeled class (Figure 2.8). The idea of using pattern recognition in prostheses was first introduced in mid-1960s and has been researched extensively in the past two decades. Current pattern recognition-based control algorithm, given conducted in an ideal, controlled environment, has achieved near perfect classification accuracy. The biggest advantage of pattern recognition algorithm is its intuitive

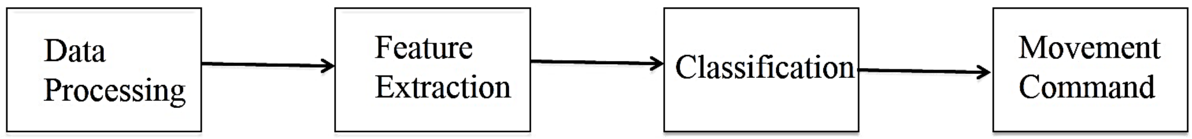

Figure 2.8: Above shows the steps required to translate EMG signals to operate pattern recognition-based prosthesis. Due to signal instability and high frequency range, EMG signal must be preprocessed and segmented to small windows. Then, selected features are calculated in order to provide information to the classifier. The classifier runs its comparison to make a decision about the most probable category (movement command) of the input (EMG signal patterns). The movement command is then used to actuate the motors to achieve the desired handgrip patterns.

control strategy, which has potential to relieve cognitive effort required by amputees to control prostheses. For example, wrist rotation in threshold-based myoelectric prostheses generally requires co-contraction followed by extension or flexion. With pattern recognition-based myoelectric prostheses, amputees can simply contract residual limb muscles the way they did to rotate their physical forearm prior to amputation. By involving physiologically relevant muscle movements to decode user’s intension, pattern recognition-based control may facilitate amputees to see their prostheses as part of their bodies, rather than a tool, leading to higher prosthesis acceptance rate.

In this thesis, pattern recognition algorithm is used as a control strategy. EMG signals were preprocessed using a 4th-order Butterworth filter with a cutoff frequency 30 – 300 Hz to remove unwanted noise. Three features, mean absolute value, waveform length, and variance, were extracted for 200 milliseconds window with 20 milliseconds overlap between windows. Most modern classification methods result in similar classification accuracy if the feature set is not varied [113]. As this project requires real-time decoding, Linear Discriminant Analysis (LDA) was chosen as a classifier for its computational simplicity.

2.5 Clinical Viability of the Pattern Recognition-Based Prostheses

Recent efforts in myoelectric prosthesis research resulted in a new generation of dexterous terminal devices that are capable of a greater number of functions than conventional open/close hand. These new prostheses typically have the ability to select among five different grip patterns and wrist rotation. Conventional threshold-based control requires a series of unnatural muscle contraction to access multiple handgrip patterns. In order to control the multi-articulated prostheses to the fullest extent, pattern recognition algorithm has emerged as a new control strategy. There has been substantial progress in developing these algorithms over the past two decades; yet, this control strategy has not been able to make a big clinical break through.

2.5.1 Factors Contributing to Decreased Classification Accuracy

In order to launch pattern recognition-based prosthesis, it is crucial to acknowledge the limitation of the system. Many studies have focused on improving pattern recognition algorithm and classification techniques, and have reached the classification accuracy of 95% [114] and above. More groups are still seeking to develop a novel algorithm and classification approach, but it is sufficient to say that the real challenge of pattern recognition-based prostheses resides elsewhere. Most of these studies were performed offline or in a controlled laboratory setting to observe the effect of different decoding approaches, but there are other sources that may cause signal instability or decreased classification accuracy in practical use of EMG pattern recognition-based control. First of such factor is the signal-to-noise ratio, which is often caused by inherent noise in electronics and motion artifact. Commonly used electronic equipment designated for pattern recognition classification is designed with high quality components, which should reduce the equipment noise. Factors such as ambient noise can be removed by using bandwidth filter, and should not affect the signal quality upon proper signal processing. Another cause of low signal-to-noise ratio is a motion artifact. While signal travels from the tissue to the amplifier, it has potential to obtain noise by poor skin-electrode interface or the movement in electrode cable. Therefore, signal-to-noise ratio is a factor that

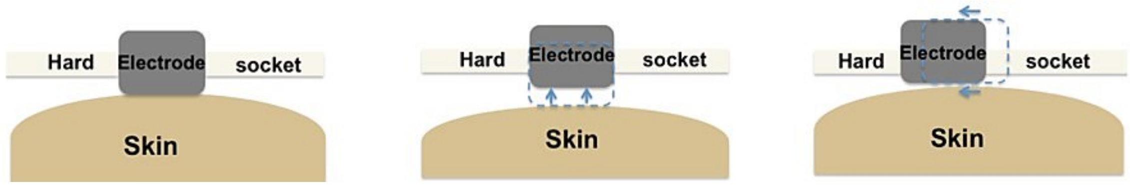

Figure 2.9: The illustration of different skin-electrode interface. From left to right; ideal interfaces, electrode lift-off, electrode migration/shift. The ideal skin-electrode interface requires stable contact between the two. The electrode lift off can be caused by improper socket fit or change in volume of the muscle during contraction. The electrode migration may result from excessive sweat, intensive movement, or the varying limp position with high gravitational load.

should be controlled by thoughtful design and setup of instruments. Second factor that may induce decrease in classification accuracy is change in skin condition. It is not uncommon for prosthesis wearers to experience sweating in their residual limb, which decreases skin impedance. Although sweat affects EMG signal in a positive way by increasing electrode conductivity, this causes post-sweat EMG signals to deviate from the trained classifier and result in misclassification. Moreover, excessive amount of sweat may lead to electrode migration (Figure 2.9) or short circuit. Change in volume and shape of the muscle during active movement of the limb has similar effect. When electrodes shift or migrate, they no longer detect the same set of motor units thus classifier cannot be trusted with confidence. Even though using intramuscular electrode would be the best solution to minimize signal variance caused by electrode-skin contact, it is difficult to justify the use of invasive, uncomfortable technique to amputees. With surface EMG, complication regarding electrode-skin contact can be minimized by appropriate fit of the liner or socket. Third factor that challenges pattern recognition classification accuracy is the posture variance (e.g. limb position effect). Recent literature has addressed that EMG features are sensitive to limb positions and classification accuracies decrease when posture other than the one where supervised learning occurred (i.e. calibration) is assessed [115]. Some have proposed to create a separate motion classifier with accelerometer input and to train in all of the interested positions [116]. Despite the fact that classification accuracy will see improvement, such second-stage classifier mechanism will substantially increase the calibration duration and be deemed cumbersome to amputees. Understanding the effect of posture variance in EMG classification and developing an algorithm that can predict the signal behavior in different postures based on minimum number of calibration data is the key to resolve this challenge. Lastly, the user effort or intent may affect the pattern recognition classification accuracy. This is a factor that cannot be controlled by the developers of prosthesis or programmers of algorithm and classifier. Implementation of adaptive classification method is one possible solution for reliable classifier [117], yet, further research needs to be conducted to determine the cost and benefit of this method. Consequently, this is the one element that amputees can influence to maintain good control of pattern recognition-based prostheses.

2.5.2 Effect of User Training in EMG Classification

In order to provide high level of classification accuracy for an extended period of time, the user must provide signal patterns that are consistent and easily distinguishable. The easily distinguishable EMG signal patterns indicate the movement classes in the feature space of a classifier that are clearly separable. The consistency signifies user's ability to generate the signal patterns repeatedly. In previous Master's work, MyoTrain, the effect of user training has been verified with real-time decoded virtual prosthesis [109]. In his study, four transradial amputees received one-on-one virtual training in a controlled environment for 10 sessions. Upon training, their average classification accuracy improved from 84.5% to 95.0% ($p<0.01$) [109].

2.5.3 Classification Accuracy and Real-World Performance

While effect of user training evaluated with MyoTrain is a breakthrough finding, the limitation lies in that this study was done in a controlled environment. The EMG signals were obtained by putting an electrode-embedded silicon cuff on amputees' residual limb, which was connected to the external data acquisition box. The subjects were seated and kept their elbow on the chair, so that the posture is controlled. Then, the subjects were evaluated while attempting to follow the visual cues presented, which were presented 3 repetitions at random for 5 seconds. In activities of daily living, amputees do not flash one movement command after another for 5 seconds. Rather, even a simple motor task with a myoelectric prosthesis requires systematically compounding movement classes.

Classification accuracy is the measure of capacity, rather than the performance. Although these two words are often used interchangeably, there is a clear distinction between the two. According to Merriam-Webster dictionary, capacity is defined as an ability or power to do something, whereas performance is defined as the act of doing something. In a rehabilitation standpoint, capacity is one's potential for functional performance, and performance is what an individual actually does in a real life situation. Training to produce high classification accuracies is not obsolete, however, it only bases its measure of success on how capable one can be in executing different movement commands without considering the effect of dynamic motor control in real-world usage. Although different algorithmic approaches and its resultant classification accuracies have been explored in depth, little study has been conducted to determine the functional relevance of classification accuracy. In a recent study on classification accuracy and prosthesis usability, there was a weak relationship between accuracy and usability scores [118]. In another study, the performance was seen to improve with decreased classification accuracy [119]. Similar to other motor learning and rehabilitation, the training effect of isolated movement (myoelectric training to generate handgrip patterns in a controlled posture) will have limited transfer to functional activities. This finding indicates that there is a need for better training method that enhances the performance as well as capacity of the intended users.

2.6 Objective

The more meaningful training and evaluation of pattern recognition-based myoelectric prostheses control involve the use of task-specific functional tasks in variety of positions. Different limb positions will impose different physiological changes in EMG recording sites due to gravity, muscle contractions, and the distribution of socket load. With the posture variance being one of the factors that affect classification accuracy [116], it is logical to expose amputees to this variability during training period. For example, a task of moving an object from one place to another requires a prosthesis to stay in a desired position or grasp until target location is reached. Once arrived to a different location/posture, amputees must generate signal patterns that do not deviate from the ones provided during classifier training. If the grip becomes loose in transition, amputees will receive visual feedback in the form of an object falling to the ground. The repetitive training in VR will enable amputees to identify and generate signal patterns that are least affected by varying limb position. By practicing object interaction in virtual environment, amputees can experience cognitive and motor commands involved in performing tasks, as well as exercise compounding movement classes with sequential pattern recognition-based control. The goal of this project is to develop a task-specific virtual training system and evaluate its efficacy on improving pattern-recognition based myoelectric prostheses control while determining relationship between virtual reality and real-world performance.

Chapter 3: Study Design and Equipment

3.1 Study Design

The study was designed to demonstrate the effectiveness of task-specific virtual training in the real-world pattern recognition-based prostheses control and determine a relationship between the real-world (RW) and virtual reality (VR) performance. Due to lack of amputees fitted or planning on being fitted with pattern recognition-based prosthesis, there was only one amputee subject for the testing. Able-bodied subjects were recruited to simulate naïve amputees' scenario, as literatures has indicated that able-bodied subjects have similar motor learning behavior as amputees [100]. Instead of customized socket that amputees use, an able-bodied prosthesis that fit various range of forearm thickness was fabricated. The same hardware as the amputee subject's pattern recognition-based prosthesis was used to sense, amplify, and decode the electromyography (EMG) and control the wrist rotator and the terminal device. The study was conducted at the Infinite Biomedical Technologies (Baltimore, MD) under approval of Johns Hopkins Institutional Review Board.

3.1.1 Subject Demographics

There were five male and three female able-bodied subjects, aged between 18 and 25. All of them had dominant arm on the right side. One of the able-bodied subjects had a moderate exposure to pattern recognition-based virtual prosthesis, but no one had prior experience of using pattern recognition-based prosthesis. One trauma-induced transradial amputee subject participated in the study. He is over the age of 60, and received his amputation 7 years ago on his non-dominant hand, right hand. He had used body-powered and single-DOF myoelectric prostheses prior to being fitted with pattern recognition-based myoelectric prosthesis 5 months ago. He received few sessions of occupational therapies for the first three months and had been wearing his pattern recognition-based prosthesis for 4-5 hours a day. Another trauma-induced transradial amputee subject was interviewed for qualitative assessment of the task-specific and game-based virtual training system. She received her pattern recognition-based myoelectric prosthesis 12 months ago, however, she had little time to utilize the device due to technical difficulties with socket fit and electrodes. Her occupational therapies were ongoing during her virtual training, thus she did not qualify for quantitative analysis in the study.

3.1.2 Training Scenarios and Evaluation Measures

To make the virtual reality (VR) evaluation relevant to the real-world (RW) evaluation, the same functional measures were used in both environments. The scale of the environment was matched to create the same functional difficulty in both environments. Both functional measures are task-specific, goal-oriented evaluations.

3.1.2.1 Modified Box and Block Test (MBBT)

The first functional measure is a modification of widely used motor functional assessment, the Box and Block Test. The conventional Box and Block Test uses a kit that is composed of a wooden box dimensioned in 53.7 cm in length, 25.4 cm in width, and 8.5 cm in depth with a partition in the middle that divides two compartments of 25.4 cm each. On the side of tested hand (right compartment in this study), 150 wooden cubes (2.5 cm) are stacked and the subject is asked to move as many blocks to the opposite side compartment as possible in 60 seconds. If the subject’s fingertips do not cross the partition while dropping the cube, it is considered failed attempt. If two blocks are transferred at once, only one block will be counted. It is a success even though the blocks fall outside the box, as long as fingertips cross the partition. Higher scores indicate better manual dexterity.

The Box and Block Test was chosen as the evaluation measure for few reasons. First, the Box and Block Test assesses upper limb unilateral gross manual dexterity. Since the study does not seek to measure one's ability to use bilateral coordination, it was best to eliminate functional measures requiring two hands. Second, the Box and Block Test does not require multiple handgrip patterns. Current pattern recognition-based myoelectric prostheses only have limited handgrip patterns (default is a "power grip)". It is possible to switch the handgrip patterns by holding open or switching the thumb position, however, this may affect the quantitative measure beyond subject's ability to execute movements he/she desires with pattern recognition-based control. Third, the Box and Block Test is simple enough to replicate in VR's limited physics engine. Other popular functional tests such as Action Research Arm Test (ARAT), Jebsen-Taylor Hand Function Test (JHFT), and Fugl-Meyer Assessment (FMA) are difficult to simulate in the virtual world. The Box and Block Test is a measure of speed, so anyone with the proper kit and the stopwatch can administer the evaluation. ARAT and FMA scores quality of movement, and it was not plausible to invite qualified personnel for the evaluation of all subjects. The Box and Block Test consists of moving wooden cubes that are light enough to have negligible effect on prosthesis control. However, JHFT includes interacting with weighted objects, and the difficulty of simulating weight of the objects and its effect on muscles via VR eliminated JHFT from the option.

There were a number of modifications made to the conventional Box and Block Test for this study (Modified Box and Block Test; MBBT). The duration of 60-second was deemed too short to reflect naïve subject's ability to control prosthesis. Therefore, time limit was extended to 5 minutes. However, in order to incentivize the subject, another condition was imposed; if 20 blocks are moved before 5 minutes have passed, the evaluation will end. The threshold of 20 blocks was determined by referencing a previously published study showing that the amputee moves 6.7 ± 1.9 blocks per two minutes on average [108]. In this way, subjects would maximize their performance to move the blocks as fast as they can. Unlike conventional box and block test, single block was placed on the compartment in order to compensate for the limitation of physics engine in VR. Each time the subject transferred the block to the opposite compartment, a new block was placed on the right compartment.

3.1.2.2 Reach-Grasp-Release Test (RGRT)

Another functional measure was designed to evaluate subjects' pattern recognition-based myoelectric prostheses control during tasks that require multiple postural changes. Unlike MyoTrain's handgrip-specific training where amputees practice in one controlled position, elbow rested on arm rest, Reach-Grasp-Release Test (RGRT) enforced using pattern recognition-based control in five different postures; neutral, upper left, upper right, lower left, and lower right. The postures were chosen to reflect subject's usual range of motion in activities of daily living. This test was design to validate whether user training can alleviate the limb position effect and enable consistent performance throughout the test.

The test involved reaching for the cube, grasping it, moving it to a target location, and releasing it to a target location. The cube was 5 cm, and appeared on top of the platform that was 15 cm in width, 15 cm in length, and 1 cm in depth. If the cube was dropped to the floor before touching the target platform or basket, the cube was returned to the original location and the score was not given. If the cube was dropped mid-way but touched the target platform or basket, it was considered a success and the score was given. Subjects were asked to move 20 cubes as fast as they could within 10 minutes. Similar to MBBT, RGRT used 2 conditions as an indication for success. The test was completed when 10 minutes had passed or when all 20 cubes had been transferred successfully. This test was originally designed with 3 varying levels of difficulty, each involving center-out, center-in, and random location task (Figure 3.1). For evaluations, only random location task was used, while all 3 tasks were used for the VR training. For the first task, the cube always appeared in the middle platform, and the subject was asked to move the cube to one of the 4 baskets that matched the color of the cube. This task focused on properly positioning the wrist to 90-degree pronation and closing the hand in the neutral limb position, moving the arm to a target location without dropping the cube, then

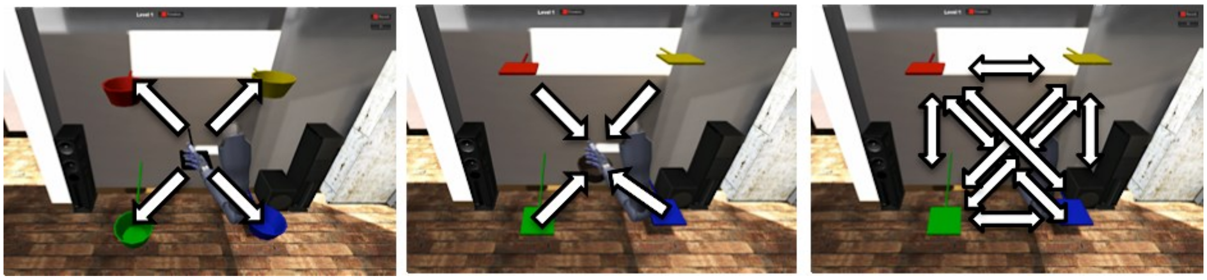

Figure 3.1: The 3 tasks of RGRT are shown. From left to right: it is center-out, center-in, and random location task. For the center-out task, the purpose is to get accustomed to executing grasp in the neutral position, which was deemed the easiest, then releasing the object at the target location. For the center-in task, the purpose is to grasp from other locations, then to release the object in the middle basket. The random location task, which was used for the virtual evaluation, both the pick-up and the drop-off location are random, therefore it enforces different handgrip patterns in all locations.

opening the hand to release the cube. For the second task, the cube appeared in one of the 4 platforms, and the subject was asked to always move the cube to the middle basket. This task focuses on properly positioning the wrist to 90-degree pronation and closing the hand in postures other than the neutral limb position, moving the arm to the neutral limb position, then opening the hand to release the cube. For the third task, the cube appeared in any of the five platforms, and the subject was required to move the cube to one of the 4 other platforms that matched the color of the cube. Once the subject successfully released the cube at a target location, a new cube was given in the same location (i.e. previous drop-off location becomes a pick-up location for the next cube). This minimizes unnecessary gross movement, so that evaluation is focused on one's ability to use pattern recognition-based control in multiple postures.

3.1.2.3 Performance Metrics

The development of task-specific virtual training had an underlying belief that the classification accuracy does not have strong correlation to usability of prostheses in real-world application. In this study, confusion matrix was used as a visual feedback upon supervised learning (i.e. calibration), but no further analysis on class separability or classification accuracy was performed. In assessment of motor function, the two mainly used measures are the quality of movement and the speed of task execution. To find more applicable measures of prostheses control, quantitative measures such as speed of the task completion were used to evaluate the performance (Table 3.1). The success was defined by moving 20 blocks in 5 minutes for MBBT and moving 20 cubes in 10 minutes for RGRT. Since subjects may not succeed in transferring 20 blocks, test completion time could not be used for statistical analysis. Instead, speed was calculated by dividing the test completion time by the number of blocks moved within the time limit.

3.1.2.4 Game-Based Virtual Training

For the second transradial amputee subject, a simple game was developed to enable her to practice pattern recognition-based control at home. The game was modified from an open source Unity game BustAMove by Javier Quevedo-Fernández. The goal of the game was to

Performance Metric	**Unit**	**Description**
Success Rate (SR)	Percent [%]	$\frac{\#\ of\ blocks\ moved}{\#\ of\ blocks\ provided} \times 100$
Test Completion Time (TCT)	Seconds [sec]	$time\ at\ last\ block\ is\ dropped\ to\ target\ location$ $-\ time\ at\ first\ block\ is\ placed\ to\ initial\ location$
Movement Completion Time (MCT)	Seconds [sec]	$time\ at\ nth\ block\ is\ dropped\ to\ target\ location$ $-\ time\ at\ nth\ block\ is\ placed\ to\ initial\ location$
Reach-Grasp Movement Time (RGMT)	Seconds [sec]	$time\ at\ nth\ block\ is\ picked\ up\ from\ initial\ location$ $-\ time\ at\ nth\ block\ is\ placed\ to\ initial\ location$
Move-Release Movement Time (MRMT)	Seconds [sec]	$time\ at\ nth\ block\ is\ dropped\ to\ target\ location$ $-\ time\ at\ nth\ block\ is\ picked\ up\ from\ initial\ location$
Test Completion Speed (TCS)	Seconds / Block [sec / block]	$\frac{Test\ Completion\ Time}{\#\ of\ blocks\ moved}$

Table 3.1: The calculation for different evaluation metrics is summarized. Test completion time (TCT) refers to the duration it takes to move all 20 objects or until time limit is reached. Movement completion time (MCT) indicates the time it takes to execute a sequence of movement to grasp and release the object to the target location. When this MCT is divided into two segments, the time it takes to successfully grasp the cube/block without dropping and the time it takes to release the object to a target location, it is called reach-grasp movement time (RGMT) and Move-Release Time (MRMT), respectively. Finally, the average time it takes to move one block/cube is referred as test completion speed (TCS).

aim and shoot a bubble to connect 3 of the same colored bubbles (Figure 3.2). Once the match was made, the bubbles popped and the new row appeared every 100 seconds. The input for the game was five movement classes that she had on her prosthesis; rest, hand open, hand close, pronation, and supination, however, the game was created so that the subject had an option to practice additional movement classes. Default setting was pronation for aiming left, supination for aiming right, hand open to lock onto the target, and hand close to launch the bubble.

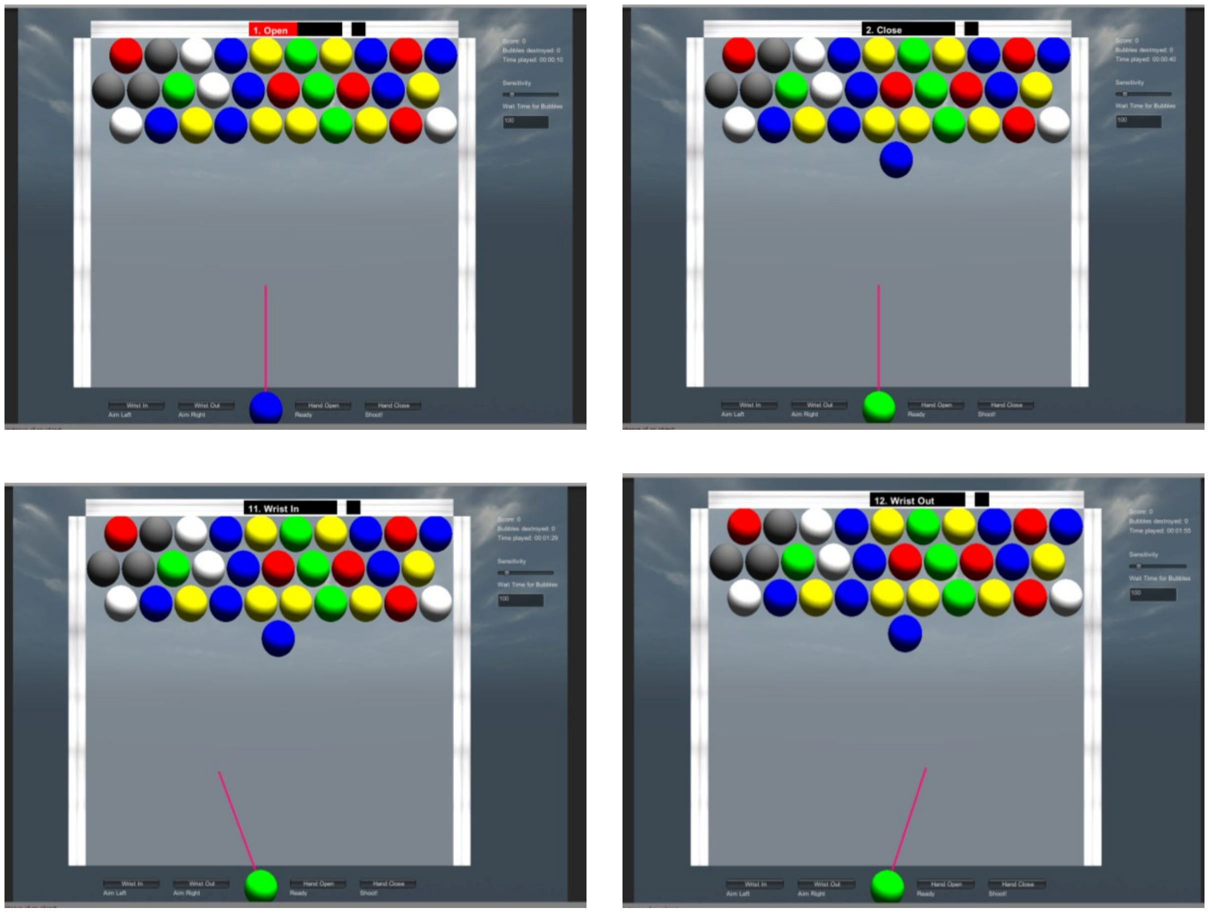

Figure 3.2: The game interface and different input commands are shown. In order to shoot the bubble, the user must open the hand to prime the shooting, until grasping-progress bar is full. Then, the hand close movement class needs to be executed until the grasping-progress bar is full, in order to shoot the bubble. Any wrong movement class will deduct the accumulated correct movement class and incrementally empties the grasping-progress bar. The bottom two represents aiming of the bubble-shooter; rotate in to aim left and rotate out to aim right.

Once the subject prepared to shoot the bubble by sending hand open movement command for a certain number of steps, the aim got locked. Until the aim was locked, “hand open” was considered a correct movement class, which filled up the initial grasping-progress bar, and “hand close” was considered a wrong movement class, which depleted the initial grasping-progress bar. Upon locking the aim, the indicator turned from black to red to remind the subject that preparation was completed. Then, “hand close” was considered a correct movement class, which filled up the second grasping-progress bar, whereas hand open, pronation, and supination were considered wrong movement classes, which emptied the second grasping-progress bar. Once certain number of hand close movement command was received, the bubble launched and the process repeated until the bubbles touched the floor. This was suitable for the amputee subject’s unintended wrist rotation. The game was not frustrating, as her wrist movement would not affect the targeting trajectory once preparation was complete, but still presented enough of a challenge because her inadvertent wrist movement would affect the launch of the bubble.

3.2 Equipment and Setup

To closely mimic amputee subject’s real-world prosthesis control, all of the hardware components used in this study are the same as the ones in amputee subject’s pattern recognition-based myoelectric prosthesis, unless otherwise noted.

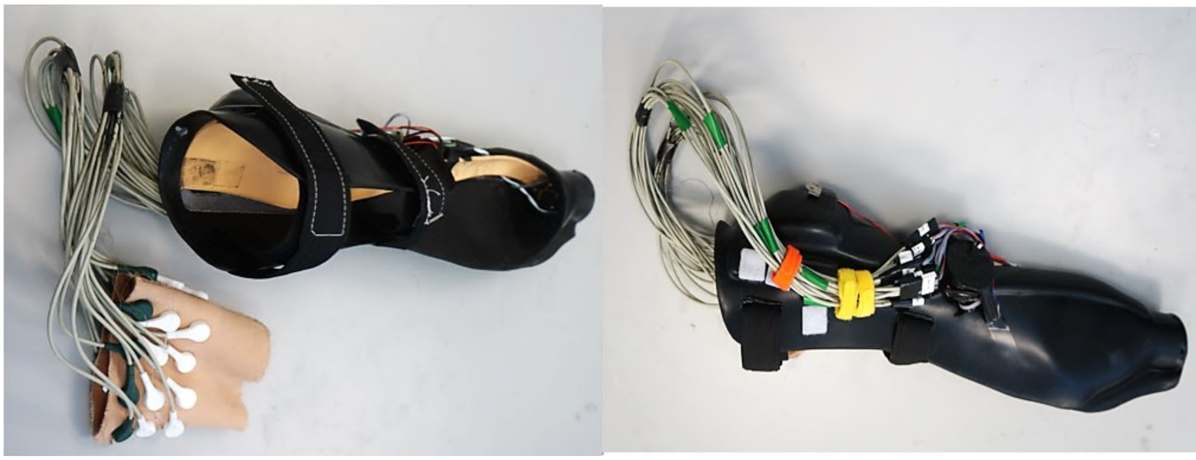

Figure 3.3: The able-bodied prosthesis with the silicon cuff, amplifier, battery, signal processing circuit, and the wrist rotator is pictured. To closely mimic amputee subject's real-world prosthesis control, all of the hardware components used in this study are the same as the ones in amputee subject's pattern recognition-based prosthesis, unless otherwise noted.

3.2.1 Equipment and Study Setup for Virtual and Real-World Environment

Most of the setup was the same for both virtual and real-world evaluation and training. Subjects wore the able-bodied prosthesis that contained electrode interface (silicon cuff, electrodes, and amplifiers), signal processing circuits, battery, and the wrist rotator at all times (Figure 3.3).

3.2.1.1 Electrode Interface

Eight Remote Myoelectrodes (Liberating Technologies, Holliston, MA) with eight pairs of EL12 metal dome electrodes (Liberating Technologies, Holliston, MA) were used to sense and amplify the EMG signals. The remote electrodes had an electrode-amplifier in circuit in a case that measured 3.1 cm in length, 1.75 cm in width, and 0.95 cm in height. Metal electrodes (0.05 cm in diameter) were separated from the case and connected with shielded cables. This type, instead of cased electrodes that have both amplifier circuit and electrodes in one casing, was more suitable for pattern recognition-based prosthesis, as their thin profile provided room to place greater number of electrodes around the residual limb. Eight bipolar pairs along with one reference electrode, total of 3 electrodes per channel, were embedded within a cuff made out of silicone rubber. The silicon cuff was rolled on to able-bodied subject’s forearm to ensure solid electrode-skin contact during use; this tight interface minimized short-term (motion artifacts) and long-term (residual limb volume fluctuations) changes in signal stability. Also, the electrodes had a fixed inter-electrode spacing of 2 cm to minimize muscle cross talk. The pairs were laid along the longitudinal axis of the muscle, and each pair was evenly distributed circumferentially across the cuff. For the amputee subject’s case, custom-made socket, which conformed to the shape of his residual limb, was used instead of silicon cuff. The bipolar pairs were differentially connected to the processing unit.

3.2.1.2 Signal Processing and Control Unit

The output of the amplifiers was connected to the analog inputs of the signal processing and control unit. Surface EMG pattern recognition algorithm ran on the 32-bit microcontroller (PIC32MX795F512L, Microchip Technology, Arizona, CA), which was located on the signal processing circuit board. EMG was sampled at 1000 milliseconds and linear discriminant analysis (LDA) classifier used the sampling rate of 100 milliseconds to detect and send the intentionality of the user in a stream of movement IDs, with each ID corresponding to the movement class. A Bluetooth (RN-42, Microchip Technology, Arizona, CA) located within the processing circuitry wirelessly transmitted the movement IDs to the PC or controlled prosthesis.

3.2.1.3 Able-bodied Prosthesis

Bypass prosthesis was designed to allow able-bodied subjects to simulate the operation of the myoelectric prosthesis. This able-bodied prosthesis (ABP) contained all the hardware components in place and encased able-bodied subject's entire distal limb starting from olecranon. The ABP was fabricated using thermoplastic copolymer by a local prosthetist upon discussing the design criteria. Two Velcro enclosures near forearm were used to account for various forearm length and thickness. To allow enough room to make handgrip patterns with anatomical hand, the ABP was left open on top while proving a place for epicondyle to rest.

3.2.1.4 Power Supply

Flexcell batteries (Infinite Biomedical Technologies, Baltimore, MD) were used to provide power to the microcontroller in pattern recognition-based myoelectric prosthesis.

3.2.1.5 Wrist Rotator

Motion Control wrist rotator (Salt Lake City, UT) was used for the study. It weighed in at 143g with 143g maximum static load, 14 in/lbs torque, and 61 rpm speed.

3.2.2 Study Setup for Virtual Environment

The components listed in this section were only used for the VR training and evaluation. To make the virtual training and evaluation in multiple postures more realistic, a combination of EMG decoded hand/wrist movements and kinematic tracking of shoulder, humerus, and elbow was implemented (Figure 3.4). First approach for kinematic tracking was to use Kinect (Microsoft, Redmond, WA) due to its ease of use and abundant open-source community. With Matlab (Mathworks, Natick, MA), an open-source package called Simulink for Kinect by Takashi Chikamasa was used to extract twenty 3-dimensional skeletal joint coordinates. The 4

Figure 3.4: The set up for virtual training of pattern recognition-based control. The subject put on the able-bodied prosthesis without the terminal and wears IMUs on the waist level, on the lateral side of the humerus, and on the lateral side of the forearm. Teensy 2.0 microcontroller, encased with the IMU on the waist level, is connected to the PC controller (Matlab) via micro-USB for data processing.

joint angles were calculated using joint coordinates and additional reference points. The calculation was based on trigonometry as shown below,

$$\Theta = \sin^{-1}\frac{\vec{A}\cdot\vec{B}}{||A||||B||} \quad (1)$$

With Java, an open-source packaged called KinectJLib by Aegidius Pluess was used to extract twenty 3-dimensional skeletal joint coordinates. However, as a result of its inaccurate interpolation of skeleton points when they were not clearly seen by Kinect's optical detector and its inability to acknowledge able-bodied prosthesis (ABP) as a part of one's body, a new approach was introduced. A fellow Master's student developed sensors to detect 4 joint angles of the interest, which resolved the aforementioned issues with the Kinect. It was composed of 3 inertial measurement unit sensors (IMU, MPU-9150, InvenSense, Taiwan) and a teensy 2.0 microcontroller. An open source package called MPU9150Lib by richards-tech was modified to calculate 4 joint angles using the same strategy as in Matlab. IMUs were positioned with Velcro fastener on the lateral side of the forearm, on the lateral side of the humerus, and on the waist near midline.

3.2.3 Study Setup for Real-World Environment

The components listed in this section were only used for the real-world evaluation. First, bebionic3 (RSL Steeper, Rochester, United Kingdom) was attached to the wrist rotator resting on able-bodied prosthesis (ABP). Ideally, subjects should be trained with the terminal device attached during the virtual training, so they can account for the weight while practicing pattern recognition-based virtual prosthesis control. However, due to limitation of ABP design that induces fatigue, the terminal device was only used for the last day of virtual training and during the real-world evaluation. The physical replication of the virtual evaluation was assembled with wooden pieces and color spray. For MBBT, the real Box and Block Test kit was used, with a circuit with FlexiForce # A201 (Tekscan, Boston, MA) on each compartment. For the

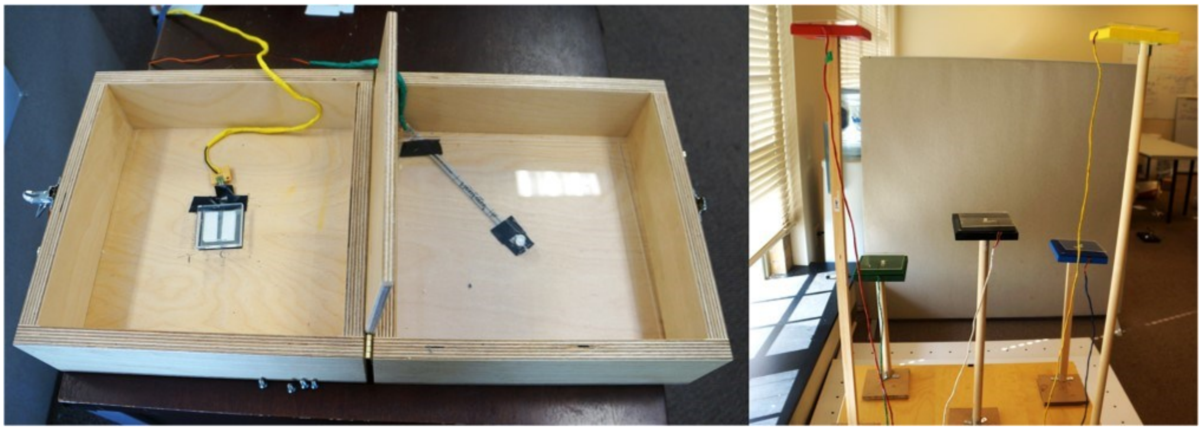

Figure 3.5: The real-world setup for the evaluation of prosthesis control. Each platform has the circuit with the force-sensing resistor, which enables accurate timing of all the incidents needed to calculate the performance metrics. The circuit is connected to the PC controller via Arduino Uno.

tested hand side, which was right side for all participants, 5 cm square acrylics was placed on top of the sensing area, while on the other side, 25.4 cm square acrylics was placed on top of the sensing area (Figure 3.5). This was done to ensure all the impact or the weight is focused on the sensing area. For RGRT, ten 5 cm cubes were spray-painted to black, red, yellow, green, and blue respectively. The wooden platforms (15 cm x 15 cm x 1 cm), spray-painted in black, red, yellow, green, and blue, were mounted on top of the wooden dowel. Each platform contained the same force sensing circuitry as MBBT, with 15 cm square acrylics on top of sensing area (Figure 3.5). Using Arduino Uno and Matlab, all incidents that contributed to calculating the performance metrics as well as the voltage output of the sensor equipped circuitry were timestamped to an Excel file every 100 millisecond.

3.3 Design of Virtual Integration Environment

Designing a task-specific training tool entailed programming in Unity, a virtual environment platform dedicated for game developments.

3.3.1 Virtual Modular Prosthetic Limb

For the study, Johns Hopkins University Applied Physics Lab's Virtual Modular Prosthetic Limb (vMPL) was used. vMPL is designed in Unity game engine, and closely mimics natural limb's range of motion with 26 DOF. It runs with VulcanX program, which commands the virtual limb to move to target joint angles in a natural manner and velocity (Figure 3.6). To interface virtual training with vMPL, Unity game engine was used to build task-specific virtual scenarios. After converting the movement commands to 23 joint angle set and integrating it with IMU-interpreted 4 joint angles (shoulder flexion/extension, shoulder abduction/adduction, humeral rotation medial/lateral, and elbow flexion/extension), 27 joint angle set was sent from VulcanX to Unity scene via User Datagram Port (UDP). With this, subjects had a full control over vMPL with the exception of the wrist flexion/extension and wrist ulnar/radial deviation, which were not commonly applicable in commercially available prostheses. The evaluation setting was scaled to the size and location of the vMPL, therefore,

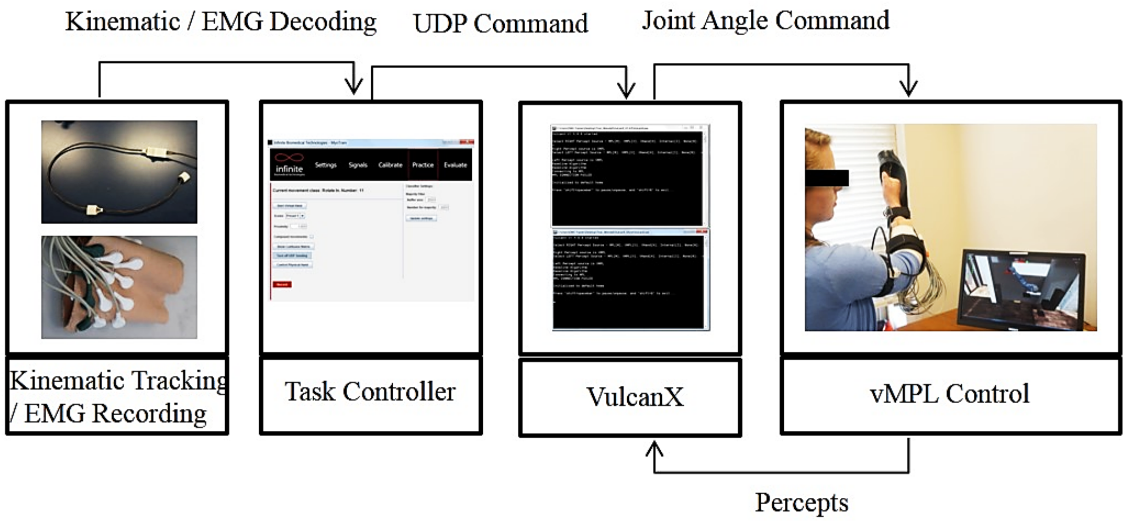

Figure 3.6: The operation of virtual prosthesis requires 4 major components: input source (IMUs and EMG), task controller (data processing circuit + GUI), VulcanX (program that commands virtual prosthesis to move in a certain way), and the virtual scene with vMPL

the relative distance and orientation between objects and a prosthesis was the same in virtual and real world settings.

3.3.2 Feedback Mechanism and User Interface

Since the virtual scene was displayed in a 2-dimensional monitor, the directional lightings, shadows, and textures were used to enhance depth cues. A properly sized interior with ground plane and walls were also used to provide linear perspective, however, the cluster was minimized to reduce visual load that may distract users from the tasks. The virtual camera was placed slightly behind the virtual prosthesis to provide the optimal view to all pick-up/drop-off locations, as conventional first person view would require a head tracking via head mounted display to properly access all the target locations in the study.

During training and evaluation, visual feedback relayed 3 pieces of information: location of the arm, location of the target (pick-up/drop-off), and the status of object grasping. First of all, the kinematic and the EMG-decoded information moved the virtual prosthesis to reflect the user's intent. Using this real-time decoded virtual prosthesis, the user could immediately map out the next movement to complete the task. Second, the target location was expressed in two ways. For both MBBT and RGRT, the target location was hinted via location of the ghost arm (detailed description in Section 3.3.3.2). For MBBT, the drop-off location turned green when the graspable object was positioned to fall to the correct side of the compartment. For RGRT, the location for pick-up always contained the cube, while the location for drop-off had color that matched the cube. To minimize confusion, all other platforms disappeared. Lastly, the status of object grasping was also displayed in two ways. When the object was grasped by the virtual prosthesis, the texture of the object changed to indicate that the object is grasped. Also, the grasping-force bar on top of the scene represented whether or not the correct movement was being executed to grasp/release the object. There was a text that reflected current movement commands, which enabled immediate realization of wrong movement class and its fix. Also, upon completion of the task, i.e. releasing the object to a target location, the numerical score that represented number of successful tasks went up to reveal the progress. At the end of the test or upon closing the program, this score was automatically saved to an Excel file for easy access and progress tracking.

Menu options were available for easy manipulation of the system setup (Figure 3.7). Normally hidden, the menus were accessible with a mouse click on the “See Option” box. Pressing “Menu” button displayed the highest score with the date and time of achievement. The “Save” button enabled to save the score as well as performance metrics recorded in the virtual scene. Level 1 through 3 could also be selected to manipulate difficulties of the task; level 1 did not impose further criteria to complete the task, while level 2 required fully pronated wrist to pick-up and level 3 required neutral wrist angle to drop-off in addition to criteria imposed in level 2. Specific to RGRT, the user could navigate through different tasks (center-out, center-in, and random location) by pressing different task boxes. The square on the right side of the task box reset the environment, i.e. score, time, and task, to the initial setting, The “View” button allowed to change the display of the virtual scene; default was similar to first person perspective described in an earlier paragraph. Pressing this button toggled between this default view and the 3-view option; looking down

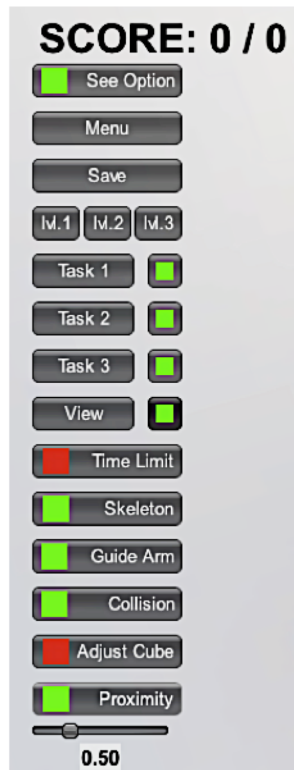

Figure 3.7: Menu options are accessible upon mouse click on the “See Option” Box. The function of each button is described in the text.

directly overhead, looking from the left side, and looking from conventional eye-level. Although this 3-view option was designed to alleviate user frustration with lack of depth cues, it is seldom preferred due to overwhelming visual load. When the “Time Limit” button was used for evaluation, the test automatically shut down upon reaching specified time constraint or required score. The “Skeleton” button hid/showed the pink skeleton that reflected actual tracking of the user movement upon pressing. “Guide Arm” refers to the ghost arm, and pressing the button hid/showed the ghost arm during the test. The “Collision” button was designed to prevent any complication in physics due to limitation in virtual environment. Upon pressing this button, the collider between the cube/block and the virtual prosthesis was disabled. For example, if the fingers of vMPL were stuck to the cube/block, this button would be pressed to free the fingers. This function had not been used since the collider was manipulated to appear or disappear, depending on the location and orientation of vMPL to prevent such unrealistic behavior. The “Adjust Cube” button was initially created to reposition the cube relative to the location of vMPL, in case the arm drift occurred. However, the problem was resolved with a different approach (detailed description in Section 3.3.3.1). Lastly, the proximity criteria for grasping logic could be adjusted to increase or decrease the distance required to grasp an object. The proximity is often increased for transhumeral cases, when EMG-decoded movement command controls the entire DOF of vMPL and the precise positioning of vMPL to a target location is deemed difficult to achieve.

3.3.3 Object Interaction

Initially, object interaction in virtual reality was set to resemble real world physics closely. Upon testing out the prototype, multiple modifications had to be made in order to make object interaction reliable, without introducing difficulties that are nonexistent in the real world.

3.3.3.1 Additional Arm for Target Latching

One shortcoming noticed shortly after implementing kinematic tracking was its stability. Both Kinect and IMUs were not sensitive enough to place the vMPL hand in an exact location to reliably grasp an object, resulting in an additional delay prior to executing movement commands. Therefore, the second arm (pink skeleton) was added to the scene. The pink skeleton represented an actual reflection of joint tracking from Kinect or IMU (Figure 3.8), while 4 joint angles (shoulder flexion/extension, shoulder abduction/adduction, humerus medial/lateral rotation, elbow flexion/extension) of vMPL latched onto a target location when pink skeleton was within the preset Euclidean distance from target joint angles set. The proximity was calculated as below,

$$Proximity = \sqrt{\sum_{i=1}^{4}(q_i - p)^2} \quad (2)$$

This allowed the arm to be optimally positioned to where it was certain to grasp an object, minimizing a delay due to the instability of kinematic tracking. Rather than using end point of wrist to determine the distance between object and the virtual hand, enforcing same joint angles set helped evaluate different subjects under same postural configuration. The vMPL would only latch to two locations at a time; the object pick-up location and the object drop-off location.

3.3.3.2 Ghost Arm for Target Configuration

To effectively utilize the vMPL latching, users needed to be aware of the target joint angle sets. With the first prototype, verbal guidance and physical demonstration were given to help identify the target joint angle sets. However, much cognitive effort was directed towards remembering the target configurations, instead of EMG control. It became evident that the users needed an additional visual reference for effective motor learning in task-specific virtual training. Transparent vMPL named Ghost Arm, which was configured and colored corresponding to the pick-up location, was displayed when the object appeared. Once the object was grasped, Ghost Arm switched to the configuration and color corresponding to the drop-off location (Figure 3.8).

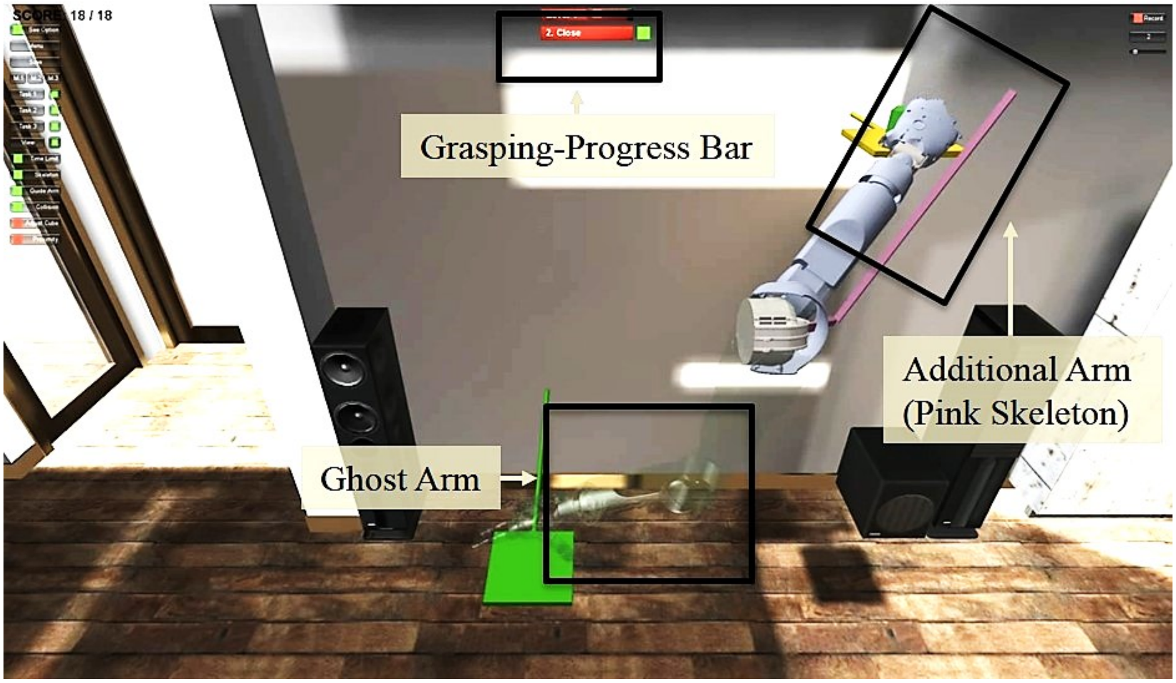

Figure 3.8: Three of the features of task-specific virtual training approach are highlighted. On the very top, there is a grasping progress bar, which determines the grasp logic. The pink skeleton is shown next to vMPL that is grasping the cube. The separation of vMPL and the pink skeleton indicates that the actual motion perceived by IMUs is within the proximity of the preset distance (in this case, 0.5), and the vMPL is latched to the target location for reliable object interaction. The last black square shows the ghost arm, which is dedicated to be a visual guidance for the next target location and required joint configuration.

3.3.3.3 Reliable Grasp Logic

Initially, the script that came with vMPL was used for object interaction. It fixed the object to the palm when predefined requirements were met. For example, when thumb and two fingers made contact with the object, the object was grasped by vMPL. However, there were many complications with this method. With vMPL still being in a developmental stage and limitation of Unity Physx Engine, vMPL experienced drifting even when it was latched to a target location. It was difficult to predict the direction and degree of the drift, thus compensation method could not be determined. This vMPL drift often times made the arm to be far away from a target joint angles set, which caused failure to meet the contact requirement at the target location, resulting in vMPL's inability to grasp the objects. Moreover, with different hand configuration at grasp, which conformed to the shape of the object and depended on location and orientation of the hand in reference to the object, it caused a frequent slippage of the object while it traveled to a target location. Therefore, a new method of object interaction was needed.

In order to resolve aforementioned issues, a less realistic but more reliable requirements were imposed for grasp logic. Movement class was sent directly to virtual scenes via User Datagram Port (UDP), in addition to VulcanX which controls joint angle configurations. The object was grasped by vMPL when (1) the palm of vMPL was in a close vicinity of the object, (2) vMPL had 90-degree pronated wrist, and (3) the grasping-progress bar was full. When first two conditions were met, the "hand close" movement command started to accumulate and this accumulation was displayed as a grasping-progress bar on the virtual scene (Figure 3.8). During this time, if "rest" movement command was received, the grasping-progress bar would not change. If "hand open" movement command was received, the grasping-progress bar would decrease (i.e. "hand close" movement class would be de-cumulated). If vMPL moved out of the predefined proximity prior to grasping an object, all the accumulation disappeared and the progress bar reset to zero. When 25 steps of "hand close" movement command had been accumulated, the grasping-progress bar turned completely red and the object became attached to the palm. 25 steps were chosen to closely mimic the response time achieved by bebionic3. Similarly, when "hand open" movement was received enough times for grasping-progress bar to be completely black after object had been grasped, the object was released from the hand.

3.3.4 Recording for Performance Metrics

To obtain performance metrics, multiple scripts with IsTrigger, OnTriggerEnter, and OnTriggerExit Unity functions were written for the virtual scene. The timer activated when the first object was initially dropped. The object entered the platform with IsTrigger function activated, and the script recorded the OnTriggerEnter time. It counted the first incident of entering the object with IsTrigger function, and only got reset when the new object appeared. If the subject dropped the cube after grasping and the cube had to be repositioned to the initial location, OnTriggerEnter time did not rewrite. This ensured the accurate measure of starting time of the movement.

When the object was grasped by vMPL, the script recorded the OnTriggerExit time. It counted the last incident of being lift off from the environment with IsTrigger function activated. If the object was dropped and had to be grasped from the platform again, the script recorded the second time the object exited the object with IsTrigger. This ensured the accurate measure of time it took to successfully grasp the object without failing.

When the object was released to a target location, the script once again recorded the OnTriggerEnter time. The target platform had IsTrigger function activated, and the incident of object touching the target platform marked the third time to be recorded by the script. In order to avoid counting the time when subject was not intending to drop, the target platform's IsTrigger function was deactivated while the object was grasped by vMPL. Only when the grasping-progress bar was completely black, the timer marked the incident. Concurrent to recording this time, the released object disappeared and a new cube appeared. This accurately recorded time taken to successfully move and release the object to a target location.

3.3.5 Unity Physx Engine

With predefined joint angle sets, the object needed to stay in the same, optimal location and orientation for pick-up. Therefore, any displacement within the pick-up platform was disregarded. Using OnTriggerStay Unity function, the object was constantly repositioned to the initial location. This function was disabled only when the object was grasped by vMPL.

Any objects or background that were not the object of interest did not collide with vMPL. With limitation in Unity Physx Engine, the hinge joint in vMPL finger joints experienced mechanical distortion such as stretching or sticking to the object. This resulted in frustration with amputees who tried the virtual training prototypes, therefore, objects that did not need to interact with vMPL, i.e. all except for the graspable object, did not collide with vMPL. However, the graspable object maintained its ability to collide with all other objects. If the subjects tried to pass through the platform with the graspable object fixed to vMPL, vMPL would be stuck as a consequence of the collision between the platform and the graspable object. This eliminated the problem with finger joint spreading or sticking, while preventing unfair advantages of discarding all obstacles that needed to be avoided in the real world.

3.4 Study Protocol

All trainings and evaluations were done in a one-on-one setting. Evaluation took 45 minutes to 2 hours depending on subject's fatigue level, while training duration was set to 60 minutes (Figure 3.9). During the virtual evaluation and training sessions, subjects faced a computer screen and were presented with a task-specific scenario to be completed with virtual prosthesis. The classifier was trained with five movement classes: rest, hand open, hand close, forearm pronation, and forearm supination (Figure 3.10). Subjects were visually prompted to mimic the randomly displayed handgrip patterns for 5 seconds each with two repetitions per movement class. Subjects were told to exert no more than 30-50 % of maximum voluntary contraction to prevent the onset of muscle fatigue. The procedure for classifier training was repeated in two postures; 0-degree shoulder flexion with 90-degree elbow flexion (i.e. the neutral posture) and 90-degree shoulder flexion with 45-degree elbow flexion (Figure 3.11). In addition to the neutral posture, the reaching up posture was added since this posture resulted in highest classification errors [116]. A combination of these two postures demonstrated the lowest overall classification errors within all postures that were within the range of movement in the MBBT and RGRT [116]. During virtual evaluation and training sessions, the virtual

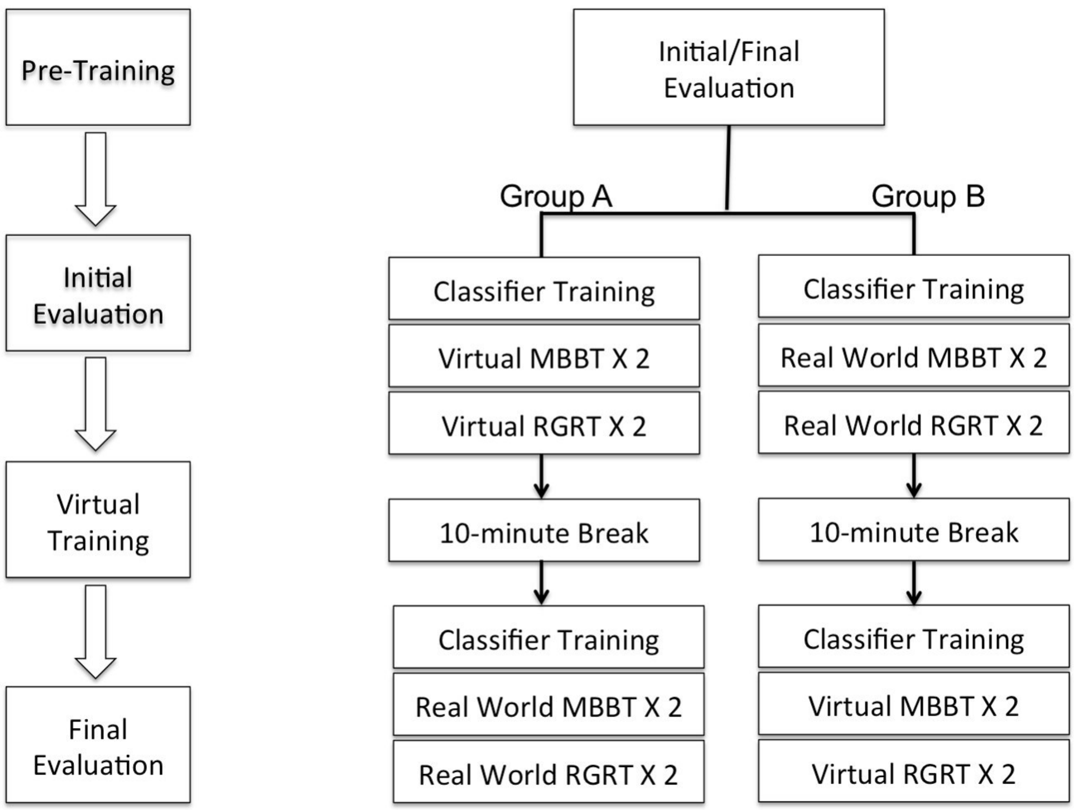

Figure 3.9: The study protocol involved pre-training, initial evolution, five virtual training sessions, and the final evaluation. The evaluation was in two parts, the real-world evaluation and the virtual environment evaluation. The classifier was calibrated with the visual cues before each environment had to be evaluated.

Figure 3.10: Five handgrip patterns used for classifier training. Subjects were instructed to apply 30-50% maximum voluntary contraction. From left to right: rest, hand open, hand close (power grip), forearm pronation, and forearm supination.

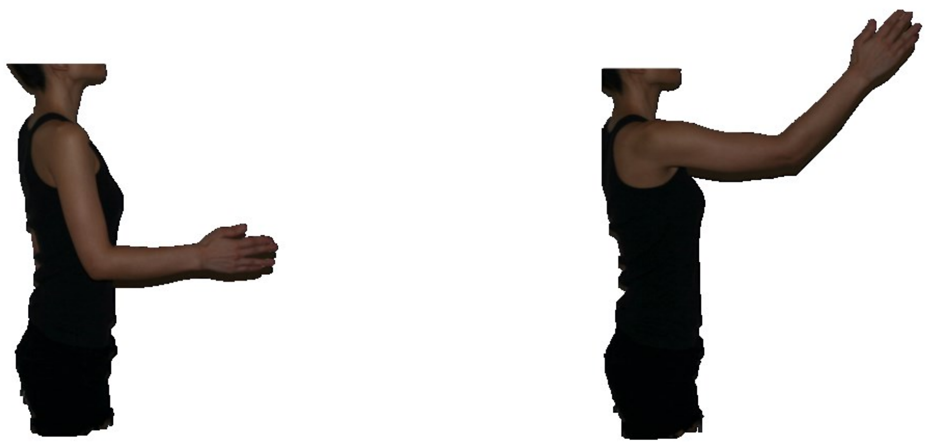

Figure 3.11: The postures used for classifier training. The neutral limb position and the reaching up limb position were used. The data from two positions were combined to create one training data set.

prosthesis animated decoded movement commands by changing hand and wrist joint angles to the joint angles corresponding to associated handgrip patterns. In addition, virtual prosthesis moved shoulder, humerus, and elbow joint angles according to kinematic information received by 3 inertial measurement unit sensors.

3.4.1 Baseline Training

Prior to the initial evaluation, all able-bodied subjects received one hour of handgrip-specific training to better understand the concept of pattern recognition-based myoelectric control. Subject trained the LDA classifier, viewed the classifier strength with confusion matrix, and then explored different handgrip patterns with real-time decoded movements of virtual prosthesis. This process was repeated as needed to find individual's unique strategy to generate easily distinguishable signal patterns and to establish above 80% classification accuracy across five movement classes. Subjects also learned to create compound movement, which required building one movement after another sequentially. For example, in order to achieve pronated hand open, subject had to pronate the forearm, go back to rest handgrip, then open the hand. This was a simple yet easily confused concept, as subjects were accustomed to a simultaneous control of anatomical hands.

3.4.2 Initial Evaluation: Day 1

Able-bodied subjects were equipped with silicon cuff embedded with electrodes, which were connected to signal processing circuit on the able-bodied prosthesis via remote myoelectrodes for signal amplification. For evaluation in the real world, both the wrist rotator and the terminal device were attached to the able-bodied prosthesis (Figure 3.12). For

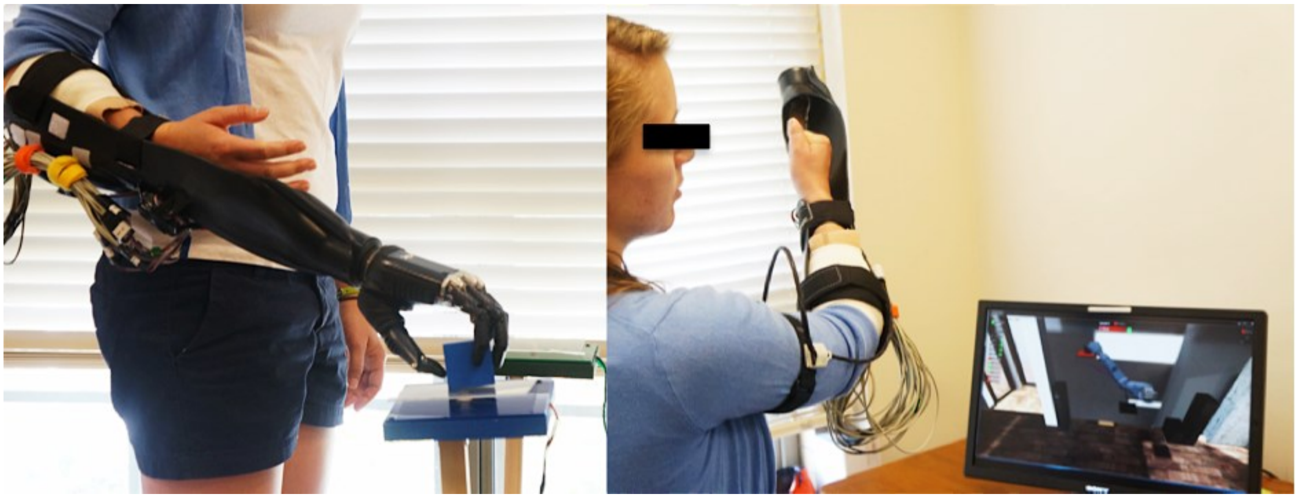

Figure 3.12: The real-world and virtual environment evaluation of an able-bodied subject is shown. For virtual training, the set up was the same as that of virtual evaluation.

evaluation in the virtual world, the terminal device was removed to prevent the onset of muscle fatigue. Also, able-bodied subjects wore inertial measurement unit (IMU) sensors on the forearm, the humerus and the waist for kinematic tracking (Figure 3.12). Information regarding hardware component is addressed in Section 3.2. Eight able-bodied subjects were randomized and divided to two groups in order to eliminate bias resulting from the order of study condition. One group performed evaluation in the virtual reality first, while another group performed evaluation in the real world first. For both groups, the Modified Box and Block Test (MBBT) was performed before the Reach-Grasp-Release Test (RGRT). Each evaluation measure was performed twice while the longer time was discarded. For the RGRT, the order of presented cube's color was randomized for each subject and the same order was used for the virtual and

Figure 3.13: The real-world and virtual environment evaluation of an amputee subject is shown. He wore his own pattern recognition-based prosthesis for the evaluation.

real-world evaluation. Maximum of 10-minute was given to practice at the start of each test. Subjects were required to rest for at least 10 minutes then re-train the classifier with the terminal device when switching from the virtual to the real-world evaluation, or without the terminal device when switching from the real-world to the virtual evaluation. Optional break of 5-minute was provided after each test. Due to terminal device malfunction, 2 able-bodied subjects had to use left hand bebionic3, instead of right hand bebionic3. To make the evaluation comparable, they used the left hand bebionic3 for the final evaluation as well.

For the amputee subject, there was no need for separate able-bodied prosthesis, as he wore functioning pattern recognition-based prosthesis. For both the virtual and the real-world evaluation, the subject had all components of the prosthesis intact (Figure 3.13). For the virtual evaluation, the movement commands were sent to VulcanX, not to the terminal device. The amputee subject also wore IMU sensors for kinematic tracking during virtual evaluation. The procedure of study was similar to able-bodied subjects, with few exceptions as follows. The subject performed the real-world evaluation first, and classifier was trained only one time since the pressure exerted on muscles contacting electrodes did not change when switching from the real-world to the virtual world evaluation. As able-bodied subjects did, the amputee subject performed Modified Box and Block Test twice then Reach-Grasp-Release Test twice, while the shorter time was selected for each test. For Reach-Grasp-Release Test, the same order of cube’s color was used for both virtual and real-world evaluation. Maximum of 10-minute was given to practice at the start of each test. The subject was required to rest for at least 10 minutes when switching from the real-world evaluation to the virtual reality evaluation. Optional break of 5-minute was provided after each test.

3.4.3 Training Sessions: Day 2 to Day 6

Both able-bodied subjects and the amputee subject received five sessions in the course of 10 days, each session lasting for 60 minutes. Able-bodied subjects received training while the terminal device was detached from the able-bodied prosthesis. The amputee subject received training with all components of his pattern recognition-based prosthesis intact, however, the decoded movement classes were only sent to the virtual prosthesis. Both abled-bodied and the amputee subject wore IMU sensors to provide kinematic input to the virtual prosthesis. The goal of this training was to improve performance in functional tasks and kinematic tracking. Most time was spent on isolating which posture resulted in misclassification and figuring out individualized strategies to resolve the issue. Since it required the virtual prosthesis to latch onto predefined joint angles prior to object interaction, it was also important to acclimate to the system's kinematic tracking so that it would not affect the task performance. The training involved practicing the Modified Box and Block Test (MBBT) and the Reach-Grasp-Release Test (RGRT) without a set time limitation. As noted in a Section 3.1.2, both tests required fully pronated wrist to grasp an object. The MBBT required subtle change in limb position, thus more time was spent on the RGRT (Figure 3.14). For the RGRT, the subjects started with center-out task stage, progressed to center-in task stage, and then finished with the random location task. The amount of time spent on each stage was different depending on individual's performance, but all subjects performed the random location stage at the end of each training session to provide information regarding their progress throughout the training period.

3.4.4 Final Evaluation: Day 7

The study setup and procedure were the same as the initial evaluation. For the RGRT, the order of presented cube's color was the same as the order used in the initial evaluation.

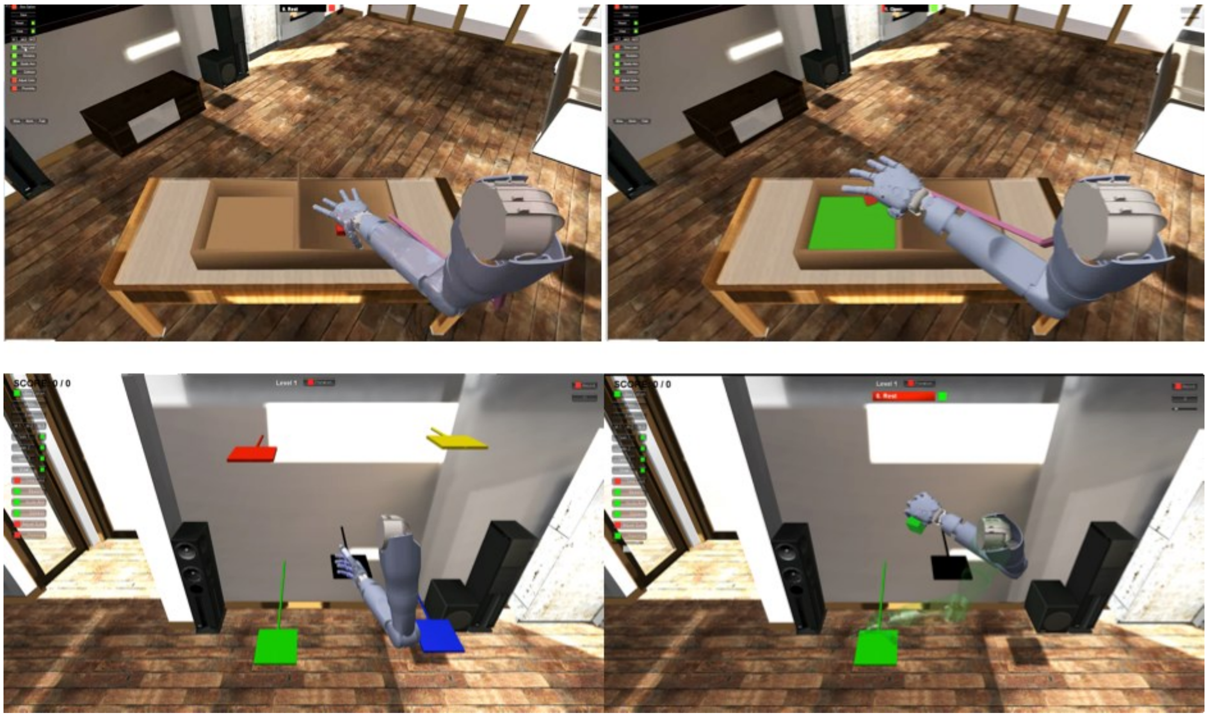

Figure 3.14: The virtual scenes of MBBT (upper) and RGRT (lower). The size of the interior and objects are relatively scaled to the size of the vMPL. Both scenes are used for evaluation and training purposes.

3.5 Statistical Analysis

Each block being transferred to a target location was referred as a task. All paired test with real-world, MBBT, initial evaluation removed one outlier, as one subject could not move any block within 5 minutes. The statistical significance was determined with 95% confidence interval (p-value < 0.05). For details on performance metrics, see Table 3.1.

3.5.1 Effect of Virtual Training: Overall Performance

Ho: $\mu 1 = \mu 2$

Test Completion Speed (TCS) from the final evaluation is the same as Test Completion Speed from the initial evaluation.

Ha: $\mu 1 < \mu 2$

Test Completion Speed (TCS) from the final evaluation is less than Test Completion Speed from the initial evaluation.

Since expectation was for virtual training to significantly improve overall performance in both virtual and real-world, one-tailed t-test was used. There was no drop out during the study, so each subject's TCS prior to training sessions was paired with his/her TCS post training sessions. The test was performed for the real-world and virtual evaluation and the virtual evaluation. It was expected to reject the null hypothesis.

3.5.2 Effect of Virtual Training: Transfer of Performance

Ho: $\mu 1 = \mu 2$

Test Completion Speed (TCS) from the virtual evaluation is the same as Test Completion Speed from the real-world evaluation.

Ha: $\mu 1 \neq \mu 2$

Test Completion Speed (TCS) from the virtual evaluation is not the same as Test Completion Speed from the real-world evaluation.

Expectation was that virtual training would close the gap between virtual and real-world performance. Other than the fact that the virtual and real-world performance might differ, there was no expectation of which one would be better than the other, so two-tailed t-test was used. There was no drop out during the study, so each subject's TCS prior to training sessions was paired with his/her TCS post training sessions. The test was performed for both the initial and final evaluation. It was expected to reject the null hypothesis before the virtual training, and accept the null hypothesis after the virtual training.

3.5.3 Effect of Virtual Training: RGMT

Ho: $\mu 1 = \mu 2$

Reach-Grasp Movement Time (RGMT) from the final evaluation is the same as Reach-Grasp Movement Time (RGMT) from the initial evaluation.

Ha: $\mu 1 < \mu 2$

Reach-Grasp Movement Time (RGMT) from the final evaluation is less than Reach-Grasp Movement Time (RGMT) from the initial evaluation.

In order to isolate the source of improvement, the time taken from the moment the object appeared to the moment the object was lift off for the last time was calculated. Only successful tasks were included. Since expectation was for virtual training to significantly improve both virtual and real-world performance, one-tailed t-test was used. There was no drop out during the study, so each subject's RGMT prior to training sessions was paired with his/her RGMT post training sessions. It was expected to reject the null hypothesis.

3.5.4 Effect of Virtual Training: MRMT

Ho: $\mu 1 = \mu 2$

Move-Release Movement Time (MRMT) from the final evaluation is the same as Move-Release Movement Time (MRMT) from the initial evaluation.

Ha: $\mu 1 < \mu 2$

Move-Release Movement Time (MRMT) from the final evaluation is less than Move-Release Movement Time (MRMT) from the initial evaluation.

In order to isolate the source of improvement, the time taken from the moment the object was lift off for the last time to the moment the object was released to a target location was calculated. Only successful tasks were included. Since expectation was for virtual training to significantly improve both virtual and real-world performance, one-tailed t-test was used. There was no drop out during the study, so each subject's MRMT prior to training sessions was paired with his/her MRMT post training sessions. It was expected to reject the null hypothesis.

3.5.5 Effect of Virtual Training: Limb Position Effect

Ho: All conditions have the same mean Movement Completion Time (MCT).

Ha: One or more conditions have a different mean Movement Completion Time (MCT).

In order to review the effect of different postures on MCT, the MCT for each shelf was separated then averaged for each subject. Only successful tasks were included and averaged. There was no drop out during the study, so each subject's time segment prior to training sessions was paired with his/her time segment post training sessions.1-way ANOVA with Bonferroni analysis was obtained. It was expected to reject the null hypothesis before the virtual training, and accept the null hypothesis after the virtual training.

3.5.6 Bias from Order of Study Condition

Ho: $\mu 1 = \mu 2$

Test Completion Speed (TCS) from the group who was evaluated in the virtual environment first is the same as Test Completion Speed (TCS) from the group who was evaluated in the real environment first

Ha: $\mu 1 \neq \mu 2$

Test Completion Speed (TCS) from the group who was evaluated in the virtual environment first is not the same as Test Completion Speed (TCS) from the group who was evaluated in the real environment first.

Since expectation was that TCS from the group who was evaluated in the virtual environment first were not significantly different from the TCS from the group who was evaluated in the real environment first, two-tailed, unpaired t-test was used. It was expected to accept the null hypothesis.

Chapter 4: Results and Discussion

4.1 Able-bodied Subjects Group

Non-paired, two-tailed t-test was performed to verify that the order of study conditions had no effect on Movement Completion Speed. In all conditions, there was no significant difference between the group who received the real-world (RW) evaluation first and the group who received the virtual reality (VR) evaluation first. Therefore, all able-bodied subjects were grouped and discussed together. Eight able-bodied subjects were labeled and referred as AB1 to AB8.

Able-bodied subjects started at a varying level of proficiency in pattern recognition-based control. During one hour of handgrip-specific training prior to the initial evaluation, some subject grasped the concept of pattern recognition-based control right away, while some did not (Figure 4.1). Although learning capacities varied, all subjects reached relatively good classification accuracies with less variance across subjects. Interestingly, high classification accuracies did not always represent better functional performance and similarly, lower classification accuracies did not always represent worse functional performance (Table 4.1, Table 4.2). For example, AB3 had accuracies below 80% in all movement classes while AB8 achieved above 90% across all movements. However, in terms of the real-world performance on RGRT, AB8 was one of the slowest. It was demonstrated that classification accuracies are only one of the components that contribute to usability of pattern recognition-based myoelectric prostheses. With high classification accuracies across all movements, one is capable of achieving but is not guaranteed to establish a good performance in the real-world applications. The observation showed that there might be no functional limitation as long as moderately good classification (> ≈80%) is present. Subjects showed disparity in the movement classes and the postures they struggled with, hence needed to explore their unique strategies to improve pattern recognition-based control during virtual training. The most frequently occurring problem was inadvertent pronation or supination during rest. Inadvertent wrist rotation is a recurrent problem for amputees fitted with pattern recognition-based myoelectric prostheses, and the issue seemed to originate from the weak intensity of the EMG signals in wrist rotation. It was often observed that subjects exerted force for a second or two during the transition period to pronation or supination, and then relaxed once the intended forearm movement was achieved. Subjects were guided to put constant force for the duration of entire 5 seconds for forearm movement classes during supervised learning, which dramatically reduced unintended wrist rotation in functional tasks.

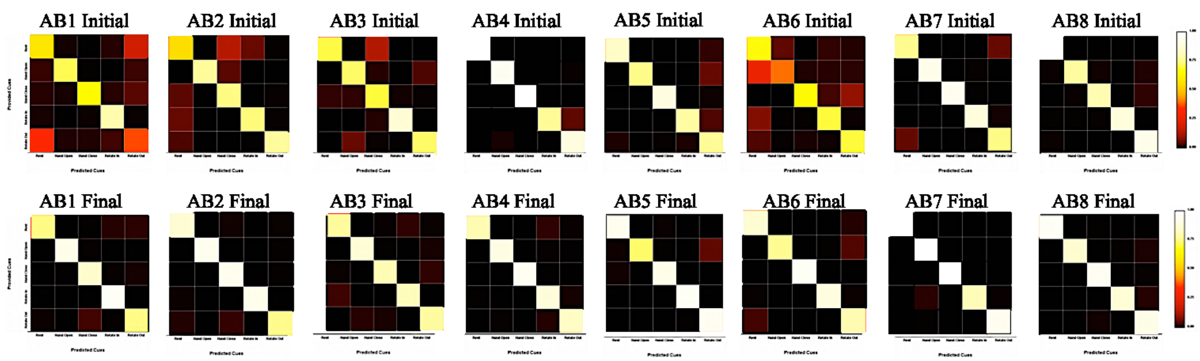

Figure 4.1: Confusion matrices of all able-bodied subjects. These matrices were taken from supervised learning for the initial and final evaluation of real-world environment. Subjects started at a varying degree of performance, but ended with a high classification accuracies across all movements.

TSC [sec / block]	**AB1**	**AB2**	**AB3**	**AB4**	**AB5**	**AB6**	**AB7**	**AB8**
Initial RGRT	29.51	13.24	10.34	7.57	15.55	42.86	7.20	13.10
Final RGRT	23.21	5.69	6.19	6.59	4.06	10.86	5.19	11.22
Improvement	6.20	7.55	4.15	0.98	11.49	32.00	2.02	1.88

Table 4.1: The Test Completion Speed of RGRT for all able-bodied subjects is summarized. Three subjects who saw the least improvement, AB4, AB7, and AB8, were the better half of the initial evaluation.

TSC [sec / block]	**AB1**	**AB2**	**AB3**	**AB4**	**AB5**	**AB6**	**AB7**	**AB8**
Initial MBBT	75.00	60.00	10.46	4.91	23.08	∞	6.05	9.13
Final MBBT	13.37	5.21	4.94	3.27	4.74	8.37	3.55	6.10
Improvement	61.63	54.79	5.52	1.63	18.34	N/A	2.50	3.04

Table 4.2: The Test Completion Speed of MBBT for all able-bodied subjects is summarized. Three subjects who saw the least improvement, AB4, AB7, and AB8, were again the better half of the initial evaluation

4.1.1 Effect of Virtual Training: Overall Performance

Success Rate (SR) of each subject was summed and divided by the number of subjects (n = 8) to obtain the average SR. In the virtual Modified Box and Block Test (MBBT), average SR improved from 71.43% at the initial evaluation to 100% at the final evaluation. For real-world MBBT, average SR improved from 42.86% at the initial evaluation to 100% at the final evaluation. Average SR of Reach-Grasp-Release Test (RGRT) improved from 71.43% to 100%, in virtual reality (e.g.,VR) and from 85.71% to 100% in real-world environment (e.g., RW). This result validates the efficacy of task-specific virtual training on pattern recognition-based myoelectric prosthesis control. All four study conditions reached 100% average SR, indicating that intensive handgrip-specific training is not a necessity for improved pattern recognition-based control (Table 4.3).

Test: Study Condition	**MBBT: VR**		**MBBT: RW**		**RGR: VR**		**RGR: RW**	
Evaluation Category	Initial	Final	Initial	Final	Initial	Final	Initial	Final
Average Success Rate (%)	71.43	100.00	42.86	100.00	71.43	100.00	85.71	100.00

Table 4.3: In the initial evaluation, there were a number of subjects who could not finish the test within given time limit. None of the study conditions reached 100% average success rate in the initial evaluation, but all study conditions reached 100% in the final evaluation. This result validates the efficacy of task-specific virtual training on pattern recognition-based myoelectric prostheses control.

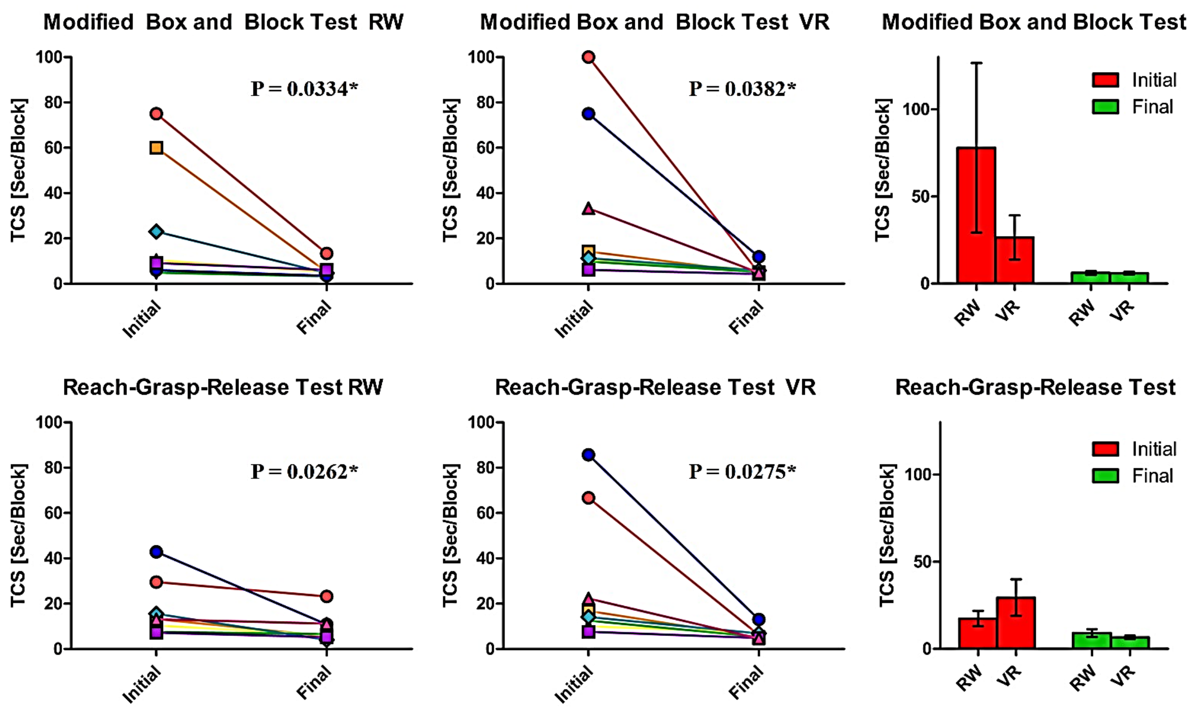

Figure 4.2: The graph represents the effect of task-specific training. The statistical analysis was performed to find the difference in test completion speed between the initial and final evaluation. After virtual training, there was a significant improvement in all 4 study conditions and environments. Despite the assumption that virtual training would be a bad reflection of the real-world performance, there was no significant between RW and VR in MBBT initial, MBBT final, RGRT initial, RGRT final. Asterisk symbol represents statistically significant difference.

For statistical analysis of training effect, Task Completion Speed (TCS) was used. For all 4 conditions, paired, one-tailed t-test was performed with 95% confidence for 8 subjects (Figure 4.2). In VR MBBT, there was a significant difference between initial and final TCS ($p = 0.0334$) evaluation. In VR RGRT, there was a significant difference between initial and final TCS as well ($p = 0.0262$). This was not only the case for VR evaluation, but also the case for

RW evaluation. There was a significant improvement from the initial to the final evaluation in RW MBBT ($p = 0.0382$) as well as in RW RGRT ($p = 0.0275$). The result reflected that task-specific virtual training improved one's ability to control prosthesis in the real-world setting. This may be the result of the change able-bodied subjects made on effort and shape of the anatomical handgrip patterns, upon exploring pattern recognition-based control in different postures. Ultimately, this unique strategy imposed by individuals led to the signal patterns that are less likely to be misclassified in varying limb positions and the faster TCS.

More subjects struggled with MBBT in the initial evaluation and with RGRT in the final evaluation. Given that user control was not ideal in the initial evaluation, it may have been easier to grasp RGRT's larger object (5 cm) than MBBT's smaller object (2.54 cm), attributing to better performance. MBBT required minimal deviation from the neutral posture, one of the postures where supervised learning occurred, while RGRT had 4 postures besides the one close to the neutral posture. Relating this to difficulties with RGRT in the final evaluation, it was predicted that one's ability to perform pattern recognition-based control in the neutral posture had improved, while the control was not as proficient in other postures. Particularly, the misclassification upon varying limb positions seemed to originate from the limitation of the able-bodied prosthesis (ABP) design. Majority of the subjects mentioned their difficulty holding the weight of ABP, especially when reaching for high shelves in RGRT. The longer it took to grasp an object from the high shelf, more muscle fatigue and mental frustration it created. This in turn resulted in misclassification and consequent delay to correct the movement commands.

4.1.2 Effect of Virtual Training: Transfer of Performance

Paired, two-tailed t-test was conducted to investigate whether there is a close relationship between VR and RW performance. Despite the assumption that the transfer of performance in one study condition to another (e.g., VR performance to RW performance or RW performance to VR performance) will be limited prior to virtual training, VR and RW showed no significant difference in TCS (Figure 4.2). In the final evaluation, as expected, no significant difference was found between TCS of VR and RW. With only 8 subjects, it is difficult to claim that the initial evaluation in VR is a good measure of one's performance in real-world or vice versa. However, the p-value in the final evaluation increased by two to three folds compared to the initial evaluation; p-value of MBBT increased from 0.3583 to 0.9240 and p-value of RGRT increased from 0.0952 to 0.3199. It is more credible to claim that after few virtual training sessions, the VR performance would become a better reflection of the RW performance. If this result of "no statistically significant difference between VR and RW" can be repeated with larger population, it will makes a strong case for the VR evaluation to be a diagnostic tool for amputees, in which clinicians determine amputees' ability to use pattern recognition-based myoelectric prosthesis in RW and assess potential improvement in amputees' quality of life with its use. More importantly, if the standardized outcome measures of prostheses control is used to validate the correlation between RW and VR performance, the result of virtual evaluation will be a critical evidence to make a medical reimbursement claim to insurance companies and justify its benefit in amputees' quality of life.

4.1.3 Effect of Virtual Training: RGMT and MRMT

Using Paired, one-tailed t-test, Reach-Grasp Movement Time (RGMT) and Move-Release Movement Time (MRMT) were analyzed to evaluate the effect of virtual training (Figure 4.3). For MBBT, a significant difference was found between the initial and final evaluation of RW RGMT ($p = 0.0184$) but no significant difference was noticed between the initial and final evaluation of RW MRMT ($p = 0.1007$.) Similarly, for RGRT, there was a significant difference between RW RGMT ($p = 0.0308$), while no statistical difference was found in RW MRMT ($p = 0.2194$). In RW evaluation of both functional tests, MRMT segment was very short in the initial evaluation. Therefore, even though improvement was demonstrated after virtual training, it was difficult to establish a statistically significant improvement. In both tests, there was a significant improvement in RGMT. This showed that subject's ability to close the terminal

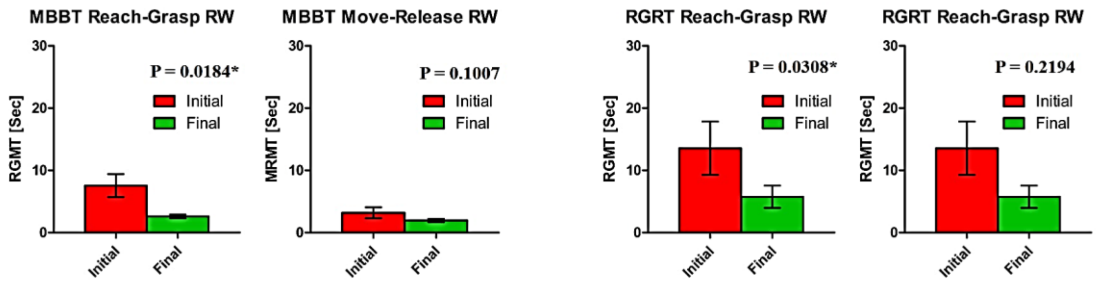

Figure 4.3: The Reach-Grasp Movement Time (RGMT) and Move-Release Movement Time (MRMT) of MBBT (Modified Box and Block Test) RW and RGRT (Reach-Grasp-Release Test) RW are presented. In both functional tests, a significant improvement was noted in RGMT, while no statistically significant difference was found in MRMT. Asterisk symbol represents statistically significant difference.

device with the able-bodied prosthesis (ABP) had increased, indicating improved prosthesis control in varying limb positions. One explanation for longer movement time in reach-grasp segment than in move-release segment is that the “hand close” grip had a smaller window to be executed. When releasing an object, the terminal device could be anywhere above the drop-off location as long as it was dropped to the target location. When grasping object, on the other hand, the terminal device had to be placed at an optimal position prior to executing the grasp in order to ensure a secure grip. Similarly, while there was no restriction on wrist angle while releasing an object, the wrist had to be pronated at about 90-degree to grasp an object.

Despite the fact that the block was positioned on the opposite side of the partition from drop-off location in MBBT whereas the cube was replaced on the same shelf as drop-off location in RGRT, longer time was required to grasp an object in RGRT than in MBBT. This result closely demonstrated one of the major difficulties subjects faced in pattern recognition-based control. The object interaction with a prosthesis requires precise placement of the terminal device, therefore, even the long-time prosthesis wearers must fixate their views to the object in order to compensate for the lack of sensory feedback. When the object interactions were required in multiple locations in RGRT, the large profile of the terminal device as well as the lengthened endpoint of ABP blocked the field of view of able-bodied subjects. Many times, subjects could not grasp an object despite correct movement command, as a result of incorrect positioning of the terminal device. Even though subjects' ability to perform pattern recognition-based control had a significant improvement, the lack of experience in precise positioning of the terminal device led to difficulties in performing functional activities in RGRT more than in MBBT. In designing of virtual scenes, assumption was made that subjects would not have difficulties placing the terminal device in an optimal configuration in RW. Therefore, the disparities in object interaction between VR and RW were produced in an attempt to eliminate obstacles in VR tasks resulted from limitation in kinematic tracking and programming engine. In VR, vMPL latched onto the target location when it got close to the object and the grasping was achieved upon establishing close proximity and correct number of movement classes (Section 3.3.3.3). This extinguished the opportunity to practice precise positioning of the terminal device for object interaction in VR, leading to difficulties in RW performance. Training of accurate positioning of the terminal device in VR will require exceptionally exact and stable motion tracking device as well as immersive first person perspective such as head-mounted display, thus the efficacy of this training strategy must be validated prior to deploying a less cost effective option.

4.1.4 Effect of Virtual Training: Limb Position Effect

1-Way ANOVA was used to examine the significance of varying limb positions. Despite the initial hypothesis that limb position will interfere with pattern-recognition control prior to virtual training, there was no significant difference in Movement Completion Time (MCT) amongst different shelf locations in both initial and final evaluation. Although individuals showed difference in MCT amongst different shelf locations, the problematic postures and locations varied from individual to individual and thus no statistically significant difference could be observed. This demonstrated that each individual was affected by varying limb positions differently, and the development of universal algorithm that can predict signal patterns from one posture of classifier training may not be possible. Such algorithm must be personalized to comprehend the unique change that varying limb position brings to the individual’s signal patterns.

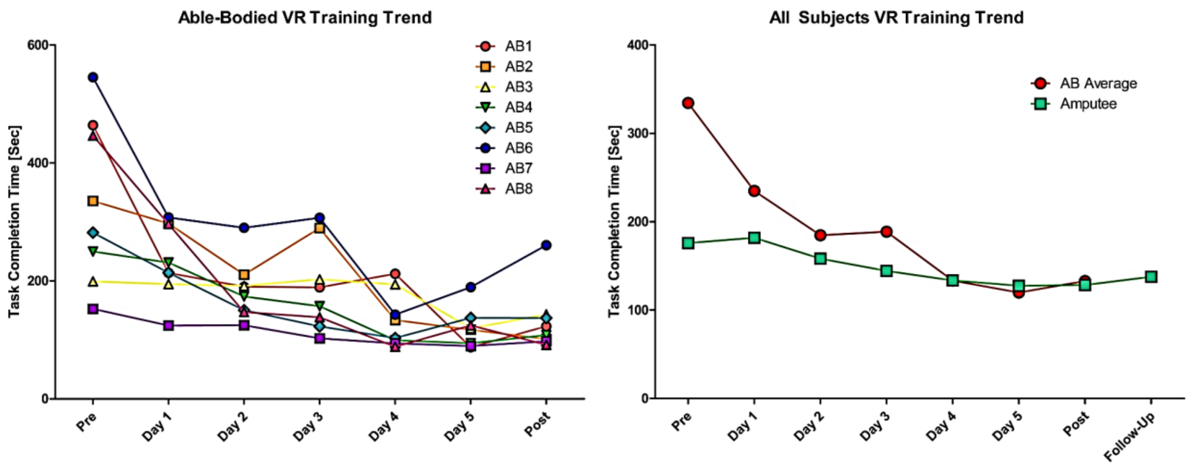

Figure 4.4: During five sessions of virtual training, Test Completion Time (TCT) for RGRT was performed at the end of each training session. The record of each able-bodied subject's (AB1 – AB8) VR performance in RGRT is on the left panel, while the averaged TCT of able-bodied subjects are graphed with the amputee's TCT on the right. Compared to the amputee's progress, the able-bodied training trend showed dramatic improvement. The amputee subject showed a good performance from the beginning and showed slow improvement. At the follow up evaluation, his performance in virtual RGRT was decreased, as reflected by increased TCT. His real-world evaluation of TCT actually improved in follow up, indicating that this decrease was likely due to his unfamiliarity with the virtual system rather than decreased functional ability. For both the amputee and able-bodied group, it is uncertain whether plateau has been reached.

4.1.5 Progress During Virtual Training

The Test Completion Time (TCT) for Reach-Grasp-Release Test (RGRT) was measured at the end of each training session (Figure 4.4). Day 5 represents TCT from the virtual RGRT with the terminal device attached to the able-bodied prosthesis (ABP). The terminal device was not functioning and was only used to acclimate subjects to the physiological change from increased weight and pressure.

Majority of the subjects showed the most improvement when going from training day 3 to 4 or training day 4 to 5. On average, the graph showed little change after training day 4. However, thorough observation of individual training progress shows that the training trend did not reach plateau for many subjects. Therefore, the maximum capability of individual may not have been reflected from five training sessions. Given that classification accuracy reached plateau after seven to ten sessions of handgrip-specific training, it will be worthwhile to replicate the study with more training sessions to see if the outcome is superior to this study's five training sessions. In addition, subject AB6 and few others experienced a significantly decreased performance on training day 5, which demonstrated subjects' difficulties with the changing weight of the ABP. As previously mentioned, subjects had different motor learning capacity. The change in weight of the ABP affected the performance for some users more than the others, hence the virtual training should contemplate to replicate the load bearing on amputee's residual limb with the prosthesis wear. EMG is susceptible to external forces, therefore, similar physiological condition should be met while amputees practice to identify their unique phantom limb movements for greater usability of the prostheses.

4.2 Case Study I: Amputee Participant

Upon being fitted with the pattern recognition-based myoelectric prosthesis 5 months ago, the amputee subject had been using his prosthesis daily. However, the use was limited to 4-5 hours a day, the maximum battery life after one time of full charge. The amputee subject's dominant arm was intact, so he often opted to use his intact limb for activities. For example, the subject would use his prosthesis for carrying a grocery bag since he felt confident about not accidently dropping the bag. However, if he had to pick up a pen from the ground or reach high up on the kitchen shelf to get a plate, the subject would almost always use his dominant, intact arm. The subject expressed that this behavior was a result of his lack of practice and confidence in using his prosthesis outside of the comfort zone.

A follow-up evaluation was scheduled 3 weeks after his final evaluation to investigate whether the training effect subsidized over time. Assuming the effective evaluation system was designed, the amputee subject's performance should not notably deteriorate and remain relatively close to the performance in the final evaluation.

4.2.1 Effect of Virtual Training: Overall Performance

Since this amputee subject had been using his pattern recognition-based myoelectric prosthesis every day for the past 5 months, the expectation was that his Test Completion Speed (TCS) in RW would show minimal improvement while VR would show a significantly better

TCS after training. Surprisingly, the subject showed improvement in both environments (Table 4.4, Figure 4.5, and Figure 4.6).

TCS [sec / block]	**Initial Evaluation**		**Final Evaluation**		**Follow Up Evaluation**	
Environment	RW	VR	RW	VR	RW	VR
MBBT	5.2	7.8	5.8	5.5	4.8	6.5
RGRT	7.5	8.8	4.5	6.4	4.7	6.9

Table 4.4: The table summarizes the amputee subject's Test Completion Speed (TCS) in all study conditions. There was minor improvement overall.

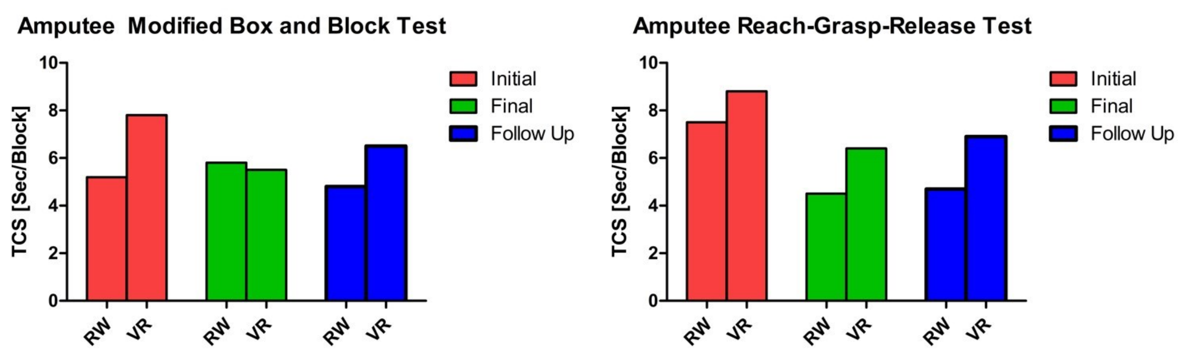

Figure 4.5: The amputee subject's training effect is illustrated for both functional tests. From the initial evaluation to the follow up evaluation, there was improvement in all study conditions. Although the Test Completion Speed (TCS) of his virtual evaluations increased (i.e. decreased performance), there was minimal change. After 3 weeks of not using the virtual training environment, the effect was sustained.

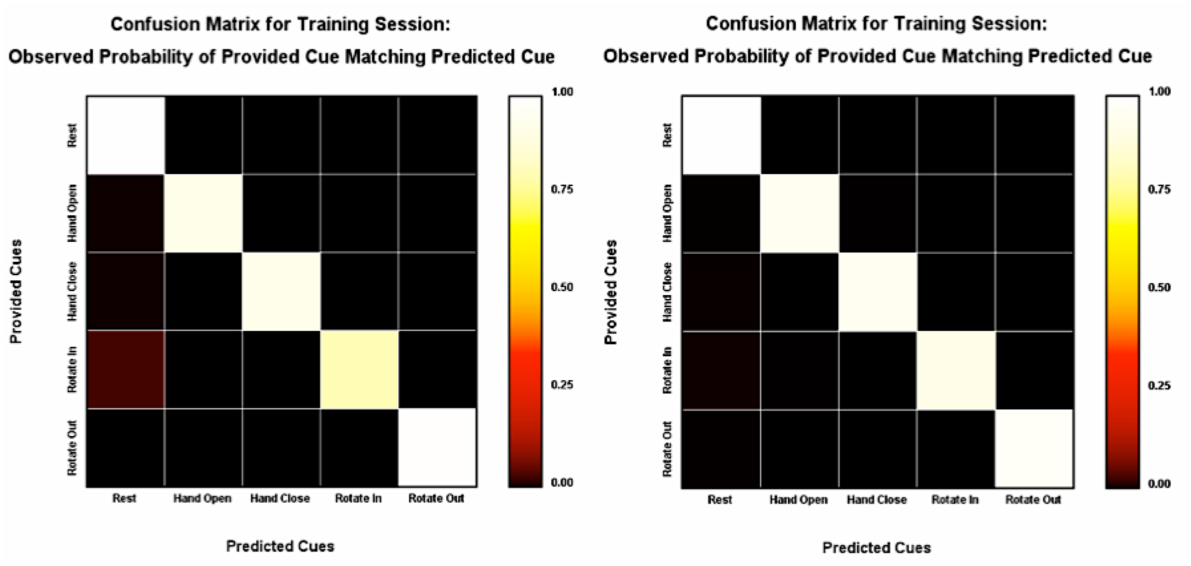

Figure 4.6: Confusion matrix of the amputee subject before and after the virtual training. The confusion matrix was taken from his supervised learning prior to each evaluation session. As the subject had been wearing his prosthesis for 5 months, he had good classification accuracies prior to virtual training. The slight confusion between pronation and rest was mitigated at the final evaluation.

The amputee subject had tried conventional Box and Block Test outside of this study, but tried MBBT for the first time on the study's initial evaluation day. MBBT was in subject's usual range of motion with his pattern recognition-based myoelectric prosthesis, yet, he still showed improvement from 5.2 sec/block in the initial evaluation to 4.8 sec/block in the final evaluation. Interestingly, the subject did relatively well in VR from the beginning, showing the change from 7.8 sec/block to 6.5 sec/block. In RGRT, which is slightly outside of his comfort zone, he showed more improvement than in MBBT. The subject's RW TCS went from 7.5 sec/block to 4.7 sec/block, shortening the time by 56 seconds. The subject's VR showed less

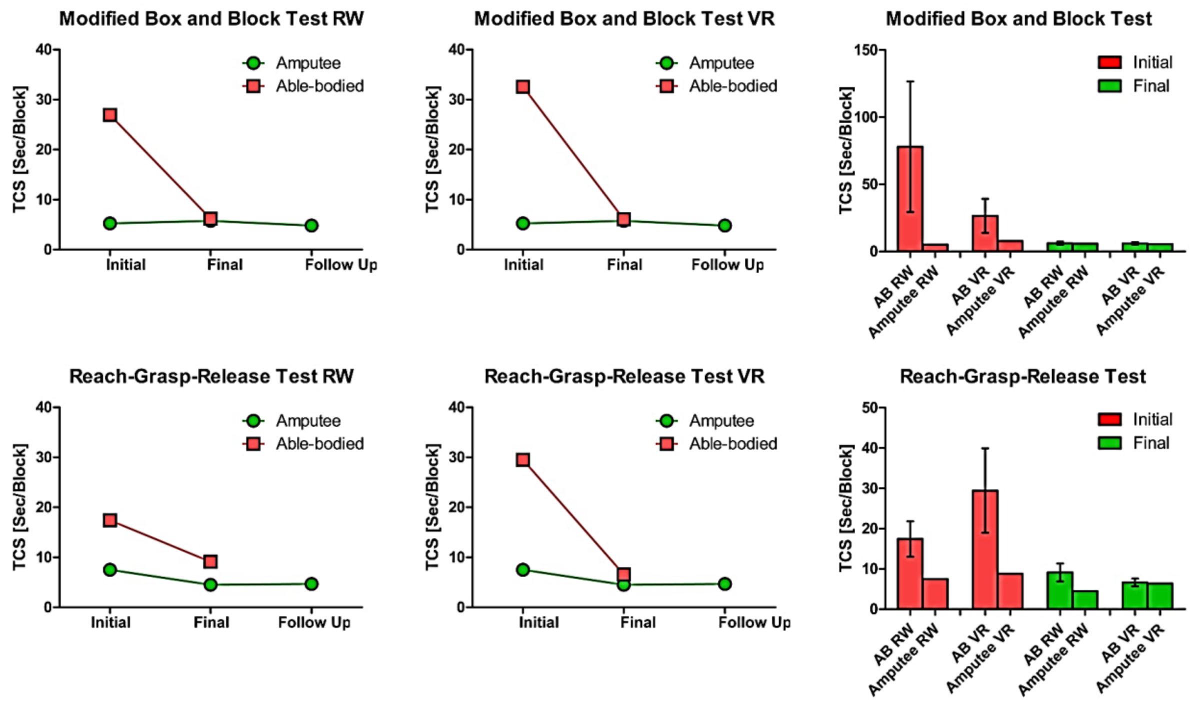

Figure 4.7: The amputee subject showed improvement in all 4 study conditions. Compared to averaged able-bodied subjects' TCT (labeled as AB), the amputee subject's performance was more consistent throughout. Also, in all 3 evaluations, the initial, final, and follow up evaluation, the amputee subject's performance metrics in VR evaluation was closely related to the metrics in RW evaluation.

improvement, going from 8.8 sec/block in the initial evaluation to 6.9 sec/block in follow-up evaluation.

In comparison to able-bodied subjects, there was an interesting finding. For able-bodied subjects, performance in RW was better during the initial evaluation and the performance in VR was better during final evaluation. For the amputee subject, he did better in RW in all cases except for MBBT final evaluation (Figure 4.7). Able-bodied subjects only tried RW prosthesis control twice, at the initial and final evaluation of this study. It is difficult to generalize without increasing amputee subject population, but from this case study, better performance was achieved with the environment that subjects had more exposure to. If amputees who have never tried pattern recognition-based prosthesis receive VR training, it is expected to closely resemble the trend of able-bodied subjects; naïve amputees will do a little worse in RW, though the degree of difference in performance level can only be anticipated after observing the trend with bigger subject population. In addition, even though the initial evaluation showed a great difference between able-bodied subjects and the amputee subject, the final performance came close in all study conditions. This illustrated that with the task-specific virtual training, it is possible to achieve the performance level of everyday prosthesis wearers.

4.2.2 Effect of Virtual Training: Transfer of Performance

In all 3 evaluations, the initial, final, and follow up evaluation, the amputee subject's performance metrics in VR evaluation was closely related to the metrics in RW evaluation (Figure 4.7). In the beginning of the study, it was expected that the amputee subject would do poorly in VR than RW and the gap will narrow upon receiving virtual training. Contrary to this belief, the difference between RW and VR actually widened for RGRT with 0.9 sec/block increase, while it followed our assumption for MBBT with 0.9 sec/block decrease. In this particular case, the amputee subject showed improvement both in RW and VR, with more improvement in RGRT that is outside of his usual range of prosthesis usage, which contributed to the increased gap between RW and VR in RGRT.

The amputee subject's VR TCS in the initial evaluation was almost as good as able-bodied subjects' average TCS after five sessions of virtual training; there was only one able-bodied subject who had better TCS better than him in the initial evaluation. It was surprising since the amputee subject's age and lack of computer game experience gave an impression that he would fall below average. This validated the previously made claim with able-bodied subjects that the performance in VR is indeed a close reflection of one's ability to use pattern recognition-based prosthesis in RW functional tasks.

4.2.3 Effect of Virtual Training: RGMT and MRMT

The difference between the amputee subject's and able-bodied subjects' Movement Completion Time originate from Reach-Grasp Movement Time (RGMT) (Figure 4.8). The amputee subject had relatively same Reach-Grasp Movement Time (RGMT) and Move-Release Movement Time (MRMT), while able-bodied subjects had much greater RGMT. As previously mentioned, RGMT measures the time taken to successfully grasp an object, which requires precise positioning of the terminal device as well as successful execution of "hand

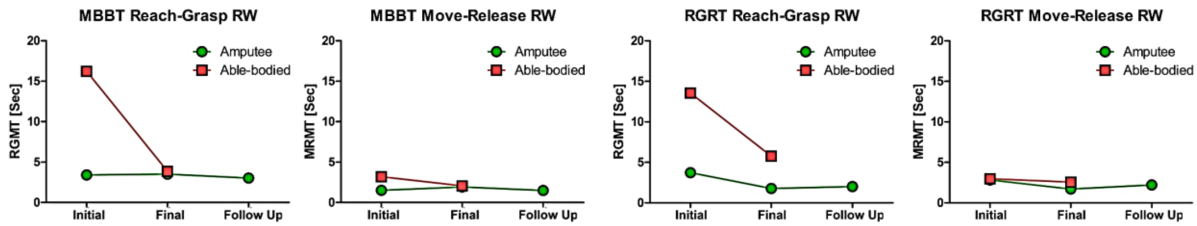

Figure 4.8: The difference between the amputee subject's and able-bodied subjects' Movement Completion Time comes from the Reach-Grasp segment, particularly in RGRT RW. The amputee subject's performance was less influenced by the RGRT, the test that utilized changing limb positions.

close" movement command. As an experienced prosthesis wearer, the amputee subject had 0.07 seconds difference between RGMT and MRMT, while able-bodied spent 3.20 seconds more on average for RGMT. This supported the previous made argument that the lack of experience in object interaction with VR training resulted in able-bodied subjects' shortcomings in RW performance.

4.2.4 Effect of Virtual Training: Limb Position Effect

The amputee subject showed more consistency amongst different limb positions than the able-bodied subjects (Figure 4.9). The variance amongst shelves, i.e. limb positions, was 0.86, 0.23, and 0.07 seconds for the amputee subject's initial, final, and follow up evaluation, respectively. While the variance of able-bodied subjects' average MCT went from 1.90

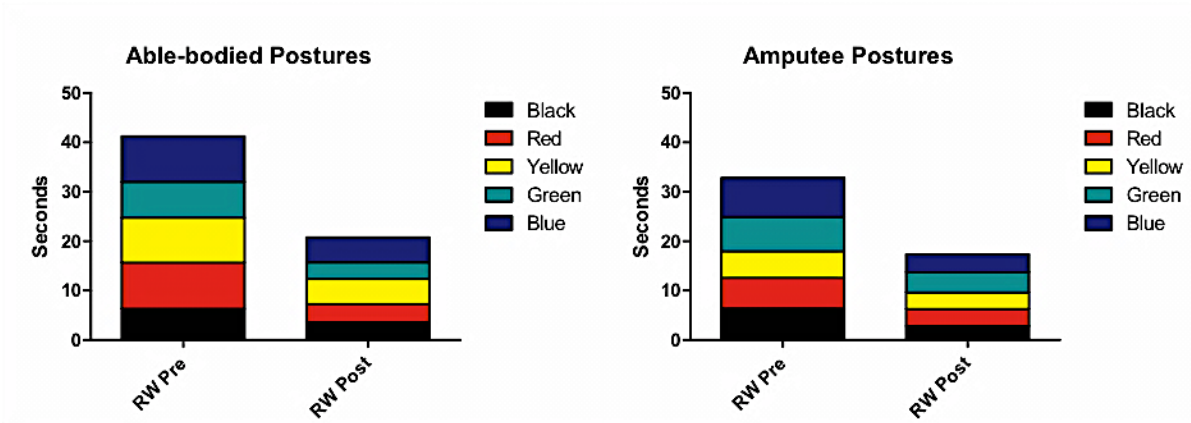

Figure 4.9: Movement completion time (MCT) of RW RGRT was analyzed by the pick-up location. The legend represents color (i.e. location) of the shelf to pick up the cube from. There was no shelf that was significantly different from the others in all shown conditions. However, averaged able-bodied subjects' MCT became more evenly distributed than before (variance went from 1.9 to 0.74), indicating that they were less likely to be affected by the limb position effect upon virtual training. In the amputee subject's case, he was negligibly unaffected by the limb position effect (variance went from 0.86 to 0.23).

seconds to 0.74 seconds, the average variance of each able-bodied subject's MCT went from 18.8 seconds to 3.2 seconds. In accordance to previous section, the disparity in troublesome postures contributed to relatively small variance in average MCT, however, each able-bodied subject showed dramatic improvement in completing tasks from multiple limb positions. Both groups were less affected by varying limb position upon virtual training, demonstrating that the limb position effect can be overcome by sufficient training.

4.2.5 Progress During Virtual Training

During five sessions of virtual training, Test Completion Time (TCT) for RGRT was recorded at the end of each training session (Figure 4.4). The amputee subject showed a good performance from the beginning and improved slowly. In the follow up evaluation, the subject's performance in VR RGRT slightly decreased, however, the improvement in comparison to the initial evaluation was still evident. The able-bodied subjects' training trend showed more dramatic improvement in VR, illustrating that the able-bodied subjects became progressively proficient in pattern recognition-based control. Although substantial difference in TCT was observed in the initial evaluation, TCT of the able-bodied subjects and the amputee subject got in proximity with each other in the final evaluation. This denoted that with task-specific virtual training, one can obtain proficiency in pattern recognition-based control that is comparable to everyday prosthesis wearers'. For both amputee and able-bodied group, the performance fluctuated throughout the training sessions, while training day 5 marked the day with the shortest TCT.

4.2.6 Interview and Comments

The amputee subject felt virtual training was helpful in general. The motion tracking was not as accurate as he would have liked, however, the subject believed it was sufficient enough to perform tasks in virtual environment. The amputee subject felt the response time of virtual prosthesis was on par with his pattern recognition-based prosthesis, and was happy with the introduction of calibrating in two postures (the neutral posture and elbow extended down posture). The subject noted that he was immersed in virtual environment after a couple sessions, and controlling virtual prosthesis felt more natural and assertive after then. The subject liked the sense of accomplishment from completing tasks in virtual environment the most, while commenting that virtual training lacked in exactness of the motions required to grasp an object. In reality, the subject could execute the pattern recognition correctly with his prosthesis but may fail to grasp or loses the object shortly afterwards. The subject felt the virtual tasks were cognitively less overwhelming, as the challenge of placing the terminal device for a secure grip was eliminated. Some of the tasks the subject would like to see in VR were activities of daily living (ADL). The subject expressed that virtual scenarios that involve carrying a cup, manipulating a small object like a key, handling utensils, and using salt/pepper shaker would benefit a new and recurrent user of pattern recognition-based prostheses. He was certain to answer that he preferred tasks to goal-directed games, as it was more practical and applicable.

The amputee subject addressed that upon receiving 10 sessions of handgrip-specific training and initial fitting in February, he did not have great control of his pattern recognition-based prosthesis outside of the posture he calibrated with. In particular, the “rest” handgrip was misclassified as pronation when the subject hung his arm completely down. The subject was hesitant to say that five sessions of task-specific virtual training made a huge impact on his prosthesis control. Following multiple occupational therapy sessions to practice hands-on control with his prosthesis, the subject slowly gained confidence and developed satisfying control of pattern recognition-based prosthesis. However, adding an arm down position to his routine calibration made the subject trust his prosthesis more. The amputee subject added that in the morning of the interview, he carried a cup of coffee with his prosthesis instead of his intact limb. This shows that the subject is more confident about using his prosthesis in activities of daily living than before.

Overall, the amputee subject strongly believed that the task-specific virtual training would be a valuable addition to the handgrip-specific virtual training he received. The subject recommended it especially for amputees who are yet to be fitted with the prosthesis, saying, "it prepares you so that it becomes less of a whole new dynamic experience."

4.3 Case Study II: Virtual Games and Task-Specific Virtual Training

One transradial amputee subject used virtual training to increase her performance in real-world prosthesis usage. This female quad-amputee subject had been having problems with pattern recognition-based prosthesis since receiving it, and decided to go through few sessions of virtual training. This amputee subject's most problematic area was the wrist wiggle. Immediately after calibrating her prosthesis, the subject's confusion matrix showed nearly 100% across all movements and she could execute all five movement classes with ease. However, when the subject interacted with objects, her wrist inadvertently rotated and affected her performance. Due to time commitment, the amputee subject visited once a week for one hour of virtual training and one hour of occupational therapy with her pattern recognition-based prosthesis.

4.3.1 Game-Based Virtual Training

For take-home use, a simple game had been provided to the subject to practice her classification accuracy (Figure 3.2, Figure 4.10). The amputee subject enjoyed playing the game at home, as no additional hardware was required and was easy to access. Even though the sensitivity could be adjusted, the subject preferred playing with the default setting, which required precise control of the wrist. The first day the subject tried the game, she had multiple occasions of misclassification during the game. For example, before executing hand open class to prepare the shooting, supination snuck in and moved the aim to where she did not intend. When shooting the bubble with hand close movement command, pronation snuck in and the subject had to hold the movement for longer period of time to make up for the lost "correct

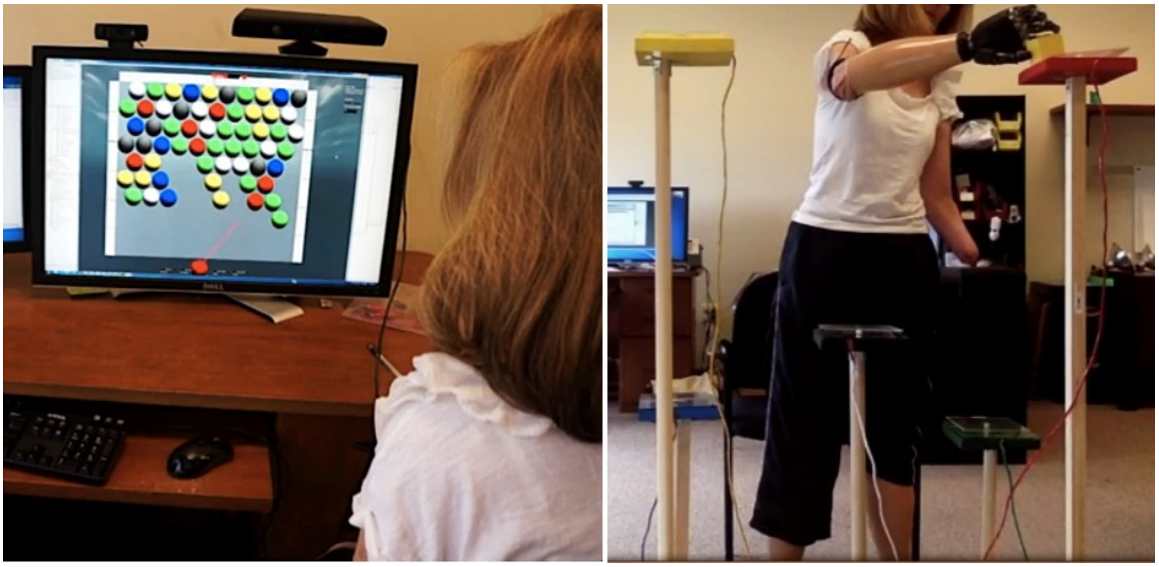

Figure 4.10: The game interface the female transradial amputee played as an at-home training tool to improve her pattern recognition-based prosthesis control. The amputee also used the real-world study set up to practice her grip control in varying limb positions.

movement class" numbers. After 3 sessions, the occurrences of misclassification decreased, and the only issue was that upon shooting the bubble and going back to rest, there was a short burst of "hand open" movement class. This was a result of sudden release of the muscle contraction; when holding a certain grip then going back to rest, opposing handgrip may become confused with the rest class if it was not done gentle. After being pointed out, this phenomenon decreased as well.

4.3.2 Task-Based Virtual Training

In addition to the game, the amputee subject was able to try VR scenarios used in the study. On first day, the subject had 13.08 sec/block for RGRT and 13.87 sec/block for MBBT. The second time, she had 7.78 sec/block for RGR and 7.06 sec/block for MBBT. On her last training sessions, the real-world setup of the study was used for her training (figure 4.10). The amputee subject tried both environments three times. The subject's best score of RGRT was 7.08 sec/block and that of MBBT was 2.49 sec/block. The subject also tried the conventional BBT for 5 minutes, with all the blocks on one side. Her speed came out to be 6.38 sec/block, which corresponds to moving 9.4 blocks in 1 minute with conventional BBT metric.

No quantitative evaluation was performed prior to her training, however, the subject's real-world performance seemed more stable than before the training. After few sessions of virtual training, the subject acknowledged having fewer problems interacting with objects using the prosthesis. Initially, the subject never used her prosthesis outside of the neutral posture, as she was afraid the misclassification might occur. After virtual training, the subject learned to use her prosthesis in a bigger range, and built confidence that she could achieve good performance even outside of her usual range of motion.

4.3.3 Interview and Comments

The amputee subject was interviewed after four training days. Four sessions of the game and two sessions of RGRT and MBBT virtual trainings were performed. When asked which of the training scenarios she liked the most, the subject answered “I will probably choose the tasks over games. The game is fun and I like the challenge of popping all the bubbles. But when I try to rotate in or out, it is difficult to move a quarter of an inch or even an eighth of an inch. Obviously, I am practicing and refining my grips, but using prosthetic hand does not require that much precision. Moving blocks seems more useful and practical for real-world use.” Even though the speed of the bubble-shooter was adjusted to reflect the Motion Control wrist rotator’s speed, it was the design flaw that the degree of precision required in the game was not often needed in RW object interaction. For the future games, it will be crucial to make the game that player can relate to in real life use. The subject also mentioned the randomness of bubble colors made the game a bit more difficult. Sometimes she would have the perfect pattern recognition-based control but the color she needed to pop the bubble of did not appear when she needed it, leading to losing the game. This issue can be resolved by adding a function to switch the color of the bubble upon executing a command, either via keystroke or handgrip patterns. One function the amputee subject liked the most in VR scene was the grasping-progress bar along with the text of current movement class being decoded. The subject commented, “it is definitely a good feedback. It lets me know right away whether I am doing the correct class. I really like that." When asked if she would have liked this training before being fitted with the hand, the subject was optimistic. She thought virtual task training "gets you used to the concept of using the hand in multiple postures." The amputee subject experienced misclassification especially when her elbow was fully extended. Since she was not a frequent user of pattern recognition-based prosthesis, the subject never realized the need for combining more than one calibration from different postures. Upon being introduced to task-specific VR training, it was easier for the subject to understand why having at least two calibrations, one from the neutral posture and another with the posture she struggled the most with, was helpful and needed.

The amputee subject felt that RGRT was more applicable to ADL that MBBT, and that MBBT was too repetitive. The subject expressed that she got through MBBT fast by getting used to moving the blocks, instead of refining her control. In RGRT, the subject was able to practice reaching and grasping for something from different heights. The only drawback she expressed was that in RW RGRT, the subject had to extend her elbow more to reach the cube, whereas in VR RGRT, vMPL latched onto a target location without too much trouble. This was a result of unstable kinematic tracking and consequent arm latching mechanism, where effort was taken to make the object interaction as easy as possible. Current requirement for arm latching is satisfied as long as the Euclidean distance is within a set proximity. Therefore, rest of the joint angles can mask the discrepancies of elbow flexion angle between real-time tracked pink skeleton and the target vMPL. To simulate tasks with different postures, it might be important to leave the main focus such as elbow extension as an additional requirement. Lastly, the subject would like to have scenes with ADL such as eating, toileting, writing, etc. In one of occupational therapy sessions, the subject tried using forks to eat brownies with her pattern recognition-based myoelectric prosthesis. The issues ranged from figuring out the configuration that provides secure grip force to the fork to applying enough force to pick up the brownies. The main problem, however, was that when the subject tried to feed herself, her inadvertent wrist rotation caused the brownies to fly out of the fork or drop to the floor. Due to such issue, the subject was mentally pressured during the therapy session. If she had been exposed to similar situation prior to receiving the prosthesis and had gone through enough virtual training, the subject would have been less hesitant about using pattern recognition-based prosthesis for eating. The current virtual scenarios require short duration of contact between prosthesis and the object. However, in ADL, one needs to hold the object for an extended period of time without sending unintended movement commands. Practicing to hold the comb without letting go while brushing hair for few minutes can be a tremendous benefit to the pattern recognition-based prosthesis users. This amputee subject said she would recommend using virtual ADL trainings until prosthesis is in hand, then practicing with a physical prosthesis upon being fitted.

Chapter 5: Future Direction and Conclusion for Amputee Rehabilitation

5.1 Pitfall of the Study Design

Despite the effort to simulate amputees' prosthesis control as closely as possible, it is inevitable that the load bearing was much bigger for the able-bodied prosthesis (ABP). The terminal device (TD) and the wrist rotator were located at the distal end of the anatomical wrist, which was necessary to encase able-bodied subject's anatomic hand. Assuming able-bodied subject's wrist was placed 2 cm in front of first Velcro enclosure, the wrist rotator and the TD would be 24.5 cm further away than where amputee would have his/her wrist rotator and the TD. With the combined weight of the TD and the wrist rotator at 557 g, it would feel much heavier and induce onset of early fatigue for able-bodied subjects than how amputees perceive it. Another shortcoming would be the fit of the ABP. Unlike amputees' custom-fit socket, single ABP had to fit all able-bodied subjects. Therefore, two 3.8 cm Velcro enclosures were used to secure the ABP on the forearm and provide tight electrode-skin contact. This created uneven distribution of interface pressure, which varied depending on the angle ABP was held.

5.2 Future Direction for Task-Specific Virtual Training

When designing virtual training system to prepare amputees for pattern recognition-based myoelectric prostheses control in the future, there are few factors that need to be considered to improve its efficacy. First, better kinematic tracking should be established. Currently, the virtual prosthesis needs to latch to target joint angle sets in order to simulate grasping. This is not only unnatural but also restricts amputees' ability to explore different limb configuration to interact with the object. It is worthwhile to consider the integration of Kinect v2, which is said to have more accurate motion tracking, and Oculus Rift (Oculus VR, Irvine, California), the virtual reality head-mounted display, for more immersive virtual training experience. The conventional first person perspective with a single monitor does not provide sufficient viewing angles to mimic peripheral vision, which results in lack of proprioceptive feedback. The Oculus Rift tracks the head movement and changes the camera angle accordingly, therefore it provides better sense of presence and proprioception. This will enable amputees to practice placing their terminal device at a proper location and orientation, an essential skill for object interaction with prostheses. Similarly, providing tactile feedback upon collision in virtual environment will offer more real-like virtual training experience. However, implementation of immersive technology should only be considered after the problem of cyber-sickness, motion sickness-like symptoms caused by the use of head-mounted display, is addressed and resolved. Second, more scenarios that closely resemble activities of daily living should be included. The response from the amputees who have tried both the game-based and the task-based interfaces was that practical tasks are more fun and useful. Simple activities such as brushing hair, brushing teeth, and holding a weighted object such as coffee mug are the type of virtual scenarios that should be considered. Handling utensils and simulation of eating scenario will be another useful activities that amputees will appreciate. The anticipation of later benefit to be experienced with the real-world prosthesis use will keep amputees motivated throughout these applicable training. Third, the use of endpoint control mechanism and the ghost arm should be considered for transhumeral or shoulder disarticulated amputees (Figure 5.1). Higher-level amputees require more actively controllable DOF, which results in a complicated control strategy. One way to compensate for the current joint angle control mechanism is the hybrid of the endpoint and joint angle control. For higher-level amputees, it will be easier to use endpoint control for gross movement that transradial amputees controlled using inertial measurement unit sensors, while joint angle control is kept for wrist and handgrip patterns. This hybrid approach will alleviate the cognitive effort and make the control strategy more natural. Also, ghost arm should be used more aggressively to promote “learning by imitation” [95] and guide high-level

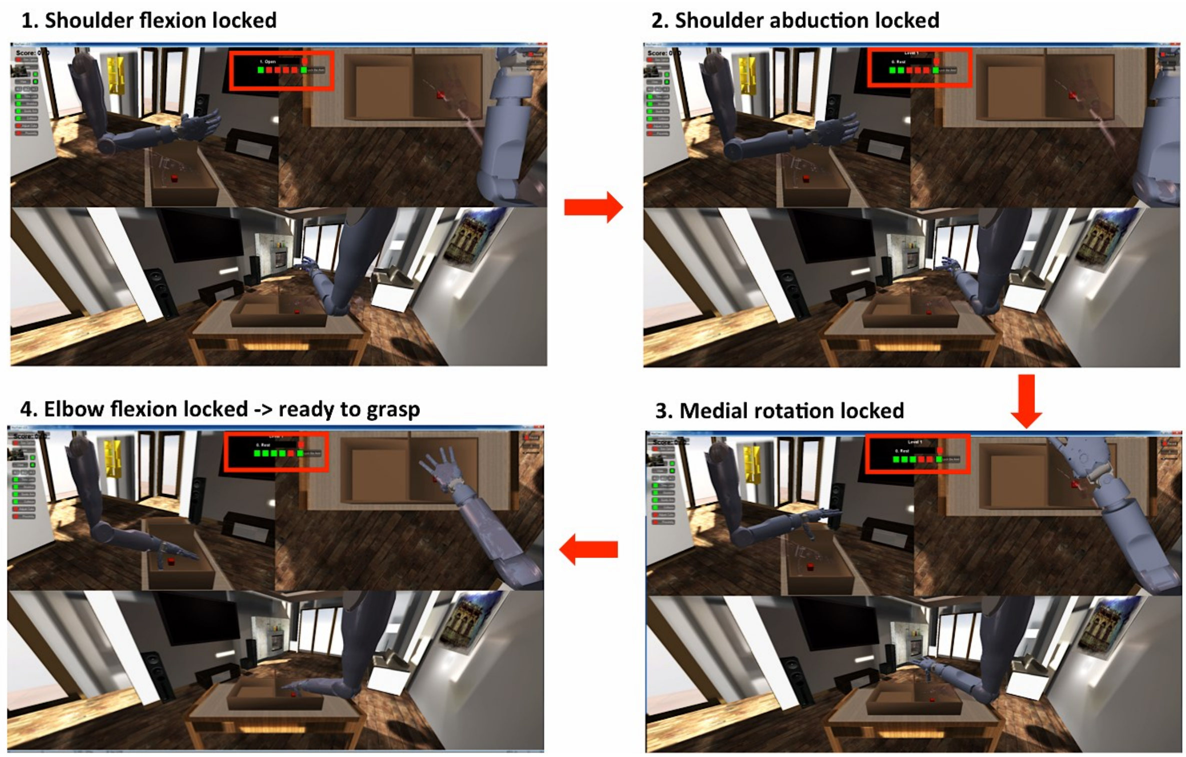

Figure 5.1: A prototype developed for a higher-level amputee's use of the virtual MBBT. Since it will require 8 more movement classes besides wrist/hand movement, the user can practice movement systematically by following the order. Using the same mechanism as the task-specific virtual scenes in the study, vMPL will latch onto a target joint angle when the arm gets into proximity to the pre-configured joint angle. Starting from the most proximal joint to the distal joint, vMPL latches onto predefined configurations sequentially. The square on the top indicates when vMPL has latched on and when the object has been grasped by displaying a green or red color, respectively.

amputees to practice intermediate postures. Current approach involves physical demonstration by the clinician administering the training. If gaming components such as randomizing target posture, imposing time limit, and scoring of the completed posture are implemented, it will motivate amputees further to spend time practicing complex sequence of movements.

5.3 Future of Upper Limb Prostheses

One of the most anticipated developments in current prosthetics field is the neuroprosthesis, particularly on sensory feedback mechanism. Upon proper training, amputees may obtain proficiency in controlling multiple degrees-of-freedom (DOF) with the prosthesis. However, the challenge remains that amputees are not capable of feeling temperature, texture, or pressure upon object interaction. An individual must pay close attention to the prosthesis while interacting with objects or people, and often times this visual feedback alone cannot provide sufficient information. This year, DARPA has proposed solicitation for a closed-loop neurprosthesis to overcome this challenge with Hand Proprioception and Touch Interface (HAPTIX) program. As a next step for Revolutionizing Prosthetics program, which developed the brain-machine interface for anthropomorphic prosthetic limbs, and Reliable Neural-interface Technology program, which established high-resolution peripheral neuromuscular interface for high performance prosthetic limbs, HAPTIX program will strive to develop an interface that can reliably decode and transmit motor signal from peripheral motor neurons and encode sensory feedback from prosthesis to stimulate peripheral sensory neurons. Success of this project will not only restore full and natural functionality of lost limb, but also encourage amputees to accept prosthetic limb as part of his/her body instead of a tool to complete essential tasks.

Another field gaining attention is the 3D printed prosthesis for the young amputees. Spending thousands of dollars on prosthesis when kids will soon outfit the prosthesis puts a tremendous financial burden on parents who have kids with congenital or traumatic loss of limbs. In recent years, a non-profit organization called e-NABLE brought forth an idea of using 3D printer to make prosthetic hands that are affordable and easily customizable. The idea emerged from developing prosthetic fingers for a young kid with Symbrachydactyly. The 3D printed finger joints are connected to the wrist component via elastic strings, so that the physical wrist movement can induce closing and opening of the 3D printed fingers. Soon after, the elbow-driven forearm was designed to provide affordable prosthetic limbs for young transradial amputees as well. Although this is in no way a replacement for the conventional prosthesis, e-NABLE arm can be used to assist essential tasks with the low cost of $50 until an individual is suited for prosthesis fitting. Additional benefit of e-NABLE is that it encourages young amputees to accept prosthesis in their life and promotes active contraction of residual limb, which prevents muscle atrophy.

5.4 Conclusion

In this thesis, the design and validation of task-specific virtual training system have been demonstrated. Despite the success in algorithmic approaches, pattern recognition-based prostheses are still restricted to the use in laboratory settings. To make pattern recognition-based prostheses clinically viable, task-specific virtual training should be conducted prior to patient fitting, as skills learned during preprosthetic training are proven to be important contributors to becoming proficient users of the prostheses. The study validated 8 able-bodied subjects' significant improvement in prostheses usability after five sessions of virtual training. Also, two amputee subjects who have gone through the training indicated that they find this training system beneficial for the pattern recognition-based prostheses candidates. Both amputee subjects expressed that anticipation of functional benefit is much greater in task-based training than the game-based training, and would like to see more tasks involving activities of daily living in virtual environment. In both able-bodied and amputee groups, virtual reality performance was a close reflection of real-world prostheses use, illustrating virtual reality evaluation's potential to be a diagnostic tool for the pattern recognition-based prostheses candidates. The limitation of the training system was that virtual reality training did not provide an opportunity to practice positioning the terminal device in a proper location and orientation for a secure grip, which is an essential skill for prosthesis use with limited sensory feedback. Therefore, the future generation of virtual training system should incorporate the use of accurate motion tracking and immersive technology such as head-mounted display to pursue practicing of this skill. With proper amputee training in virtual reality prior to patient fitting, the clinical viability and usability of pattern recognition-based prostheses are expected to increase.

Appendix:

Upper Limb Stroke Rehabilitation

A.1 Introduction

Stroke is defined as a "clinical syndrome characterized by rapidly developing clinical symptoms and or signs of focal and at times global loss of cerebral function, with symptoms lasting longer than 24 hours or leading to death, with no apparent cause other than vascular" [120]. 85% strokes are ischemic strokes, caused by blood clot and consequent blockage in artery or blood flow in brain [12]. The remaining strokes are hemorrhagic, resulting from a ruptured blood vessel that creates leakage and arises pressure on brain cells [12]. When oxygen and blood flow is interrupted, approximately two million brain cells die every minute, which can permanently damage motor, sensory, speech, or cognitive function of the brain. Approximately 80% of stroke survivors experience hemiparesis, the weakness, ataxia, heaviness, and clumsiness, on the body contralateral to the stroke lesion [7].

Research indicates that intensive, repetitive care provides the basis for motor learning and functional recovery. The repetitive execution of complex motor movements accelerates the time course and supports functional recovery [101], [102]. Relationship has been demonstrated between the amount of time the affected limb is used and the degree of motor recovery patients achieve. Increasing the amount of training time helps functional recovery and can reduce a long-term disability [18]–[22]

Increased use of the affected (or impaired) limb in activities of daily living (ADL) helps prevent or reverse learned non-use. Learned non-use is a learned suppression of movement in the affected limb that is related to the brain damage, but does not itself result from the damage of the nervous system [10]. Learned non-use develops during the early stages following a stroke as the patient begins to compensate for difficulty using the affected limb by increasing reliance on the healthy limb, which hinders functional recovery in the affected limb [11]. The best way to prevent or reverse learned non-use is to stimulate the use of patients' affected limb in a real-life situation [10]. However, the traditional therapy approaches focus on exercising isolated movements. These exercises provide limited transfer of training effect to the functional benefit in ADL

Motivation is an important factor in stroke rehabilitation. According to literature, patients' active involvement during the therapy is the key ingredient for the recovery of motor function [23], [24]. Unfortunately, stroke survivors are often reported to not only have a lower quality of life, but also experience post-stroke depression that contributes to their loss of motivation [121] and abandonment of crucial rehabilitation exercises.

A.2 Current Trend and Limitation of Stroke Rehabilitation

Most stroke research is observational, where multiple approaches are attempted then evaluated using functional assessment. The development of neuroimaging technologies such as computed tomography and magnetic resonance imaging has provided a better understanding of cerebrovascular and tissue pathology and acute treatment and secondary prevention. However, there is still insufficient evidence to prove that one treatment is more effective than any other and the best treatment method still remains obscure [122]. To date, stroke rehabilitation is partially based on theories and heavily dependent on therapist's knowledge and past experience [123].

Conventional stroke rehabilitation consists of physical and occupational therapy. Physical therapy focuses on restoring motor function of the affected limb, while occupational therapy focuses on regaining independence by learning new skills to compensate for the loss of function in the affected limb [124]. Upon being discharged from the care center, stroke survivors generally receive an outpatient care to meet with the therapist. Therapist is seldom equipped with advanced stroke rehabilitation devices, thus standard physiotherapy emphasizes practicing isolated movements to induced repetitive exercise with general progression from isometric to eccentric to concentric movement [101]. Active or passive range of motion exercise, sensory stimulation via tapping or stoking, and temporary restraint of healthy limb (e.g., constraint-induced movement therapy) are among the most widely accepted strategies utilized by physical therapists [125]. While standard stroke rehabilitation should continue to be an important part of the therapy, there is a need for an additional therapy technique to overcome its limitations. As addressed before, it has not been demonstrated which therapy may be more effective than the others in improving specific aspects of motor impairments [17], [126]. This is caused by lack of objective measures of patient's performance and progress that can determine the effectiveness of different treatment methods. Moreover, its labor-intensive nature and low-motivational repetitive exercise hinder patients' successful rehabilitation and functional recovery.

In recent years, strategies incorporating advanced technologies have gained its popularity in stroke rehabilitation research. In particular, goal-directed virtual or game environment using off-the-shelf motion sensing device such as Wii (Nintendo, Japan) or Kinect (Microsoft, Redmond, WA) has made a remarkable impact on stroke rehabilitation [127], [128]. Motion-based games enforce intensive, goal-directed rehabilitation with its motivating, enjoyable environment. However, transfer of research into commercial product has been challenging, making these novel technologies only available to selected few stroke survivors.

A.3 State-of-the-Art Stroke Therapy Methods

There are a number of stroke rehabilitation devices with novel technologies and approaches. In this section, some of the commercially available devices are described.

A.3.1 EMG Exoskeleton: Myomo

In 2002, the Myomo® e100 NeuroRobotic system was developed by a team at MIT as a prototype device that provides assistance during elbow movements in stroke survivors. Few years later in 2007, the FDA approved the commercial form of the NeurRobotic, Myomo® mPower 1000, for 510(k). mPower 1000 consists of electrodes located on biceps and triceps muscle, an elbow brace with a direct current motor, and a power/control pack that contains rechargeable batteries [129]. Designed as a feedback-based, closed-loop system, mPower 1000 facilitates motor re-learning by amplifying and rewarding patients with desired motion that is initiated by their own muscular activation. It controls the counter-balance force generation based on the amplitude of the EMG signals and amplifies the patients' attempted movement to generate assistance that is proportional to the their effort [130]. Since movement is initiated and controlled by the patients' EMG activity, the patients' brain functions as the controller to link the intention to move with the proprioceptive sensory feedback occurring with successful movement of the limb. The device can learn how best to stimulate patients with minimum assistance to maximize the active motor learning. To ensure safety, a maximum of 14 Nm of torque generation was place to avoid unsafe acceleration or forces applied to the arm. The brace has mechanical stops that restricts it from exceeding the safe range of motion, 3° to 130°, to prevent injury due to hyperextension of the elbow [130].

Myomo® mPower 1000 also comes with a 2 software programs for therapy augmentation and feedback/management. myGame® is a virtual reality-based therapeutic training system designed to encourage rehabilitation exercise in a highly motivating environment. The program allows stroke patients to have fun while performing repetitive movements and increase the use of their affected limb. Another program, myProgress®, is used to track patient's performance with objective measures. myProgress® captures measurements such as range of motion with and without assistance, duration or number of movements per session, and limb muscle exertion over time. The patients can also examine progress towards improvement over the period of therapies to maintain their motivation high. Also, its Bluetooth capability allows the clinicians to monitor patients' progress on a Smartphone. This quantitative feedback clinicians receive could optimize therapy session with their patients and facilitate evidence-based rehabilitation, unlike conventional approach based on theory or experience.

A.3.2 Functional Electrical Stimulation: Bioness

Bioness H200® is a wearable orthosis that uses non-invasive functional electrical stimulation (FES) to deliver mild electrical impulses to activate the nerves that control the muscles in the hand and forearm. It activates the muscles by applying electrical stimulation in a precise, synchronized sequence [131]. The placement of five electrodes, located on extensor digitorum, extensor pollicis brevis, flexor digitorum superficialis, flexor pollicis longus, and thenar muscles, is determined by clinicians to ensure individual's full extension and flexion of all five fingers. The electrodes are connected to a stimulator unit that delivers alternating current at a carrier frequency of 11 kHz, time-modulated to burst at 36 Hz [132]. Upon initial fitting, the clinicians may customize the training regime for patients and set the strength of stimulation based on each patient's condition.

Bioness H200® allows patients with severely affected limb with little to no hand/wrist movement to perform functional tasks with enough repetition to drive the neural repair [133]. A successful completion of these tasks without the assistance provides patients a positive reinforcement and sense of accomplishment. Moreover, use of Bioness H200® reeducates muscles over time, ultimately enforcing patients' independency from the device.

A.3.3 Assistive Orthosis: SaeboFlex

Stroke patients often have flexor hypertonia and finger extensor weakness, which makes it difficult to open their affected hand for functional grasp [134]. SaeboFlex® is an orthosis that assists hand rehabilitation to overcome flexor hypertonia. It uses a series of springs to provide resistance and assistance when grasping and releasing the grip, respectively. The design of SaeboFlex® presents patients an opportunity to perform repetitive task-specific exercise, which is proven to help motor recovery [101]. Also, it may help an individual with severe upper limb impairment to qualify for constraint-induced movement therapy, whose protocol has minimum motor criteria of active finger and wrist extension [135].

A.3.4 Research Prototype: Us'em

Many studies have shown effectiveness of increased use of affected limn with constraint-induced movement therapy, but the use of this technique is limited due to its labor-intensiveness and expensive cost [10]. The challenge emerges to develop therapy technique that motivates stroke patients to increase unsupervised use of their affected limb during daily life. Us'em is a watch-like activity monitor that provides graphical feedback of affected and healthy limb usage [136]. Unlike previously listed rehabilitation devices, Us'em does no aid the completion of patients' intended movement. Instead, it facilitates subject-driven, active movement that is more effective than robot-driven, passive movement [137]. Using accelerometer, Us'em displays the ratio of movement in the affected limb compared to the healthy limb on the screen of the watch-like device. The limitation of Us'em is that the accelerometer is not always a good representation of movement detection. For example, if the user is walking and the affected limb moves as a part of gait function, this movement will be registered and calculated as part of the affected limb usage ratio.

A.4 Smart Sleeve Design Proposal

The overall goal of this project is to develop a surface electromyography (EMG) and motion sensor-integrated activity monitor, Smart Sleeve, for post-stroke upper limb rehabilitation. It has been proven that intensive, repetitive motor rehabilitation is the key to regaining upper arm functionality [101]. This requires patients to be incentivized to utilize their affected limb even after the completion of inpatient care at the rehabilitation clinic. However, the repetitive nature of rehabilitative exercise, lack of meaningful feedback, and potential post-stroke depression discourage patients from dedicating effort to exercise their affected limb, resulting in a condition called learned non-use. Moreover, it has been noted that stroke patients overestimate the use of affected limb during activities of daily living, leading to clinicians reeving inaccurate, subjective data. Therefore, there is a pressing need for a rehabilitation system that provides meaningful, quantitative feedback that facilitates the patients to be actively involved in their therapy.

APPENDIX: UPPER LIMB STROKE REHABILITATION

To date, the accelerometer has been the most common tool to monitor activity due to its ease of use. However, it has inherent limitations in differentiating between an active versus passive movement or a loaded versus unloaded activity [138]. For example, when the user changes his/her posture from standing to sitting, the accelerometer will recognize this as an activity of the limb, though the user put no intentional effort to move the arm. In contrast, electromyography (EMG) sensors provide a practical way of differentiating these movements and can also specify individual muscle activity level. Therefore, the EMG/Accelerometer hybrid sensor scheme will be an ideal approach for eliminating unintended movement to provide an accurate measure of arm usage. The scarcity of EMG-based approaches for activity monitoring has been due to the general belief that EMG techniques are not amenable to home use. This perception has likely been perpetuated because of previous sensor technologies that did not incorporate active electronics at the recording site, thereby requiring time-consuming skin preparation and immobilization of sensor leads to reduce baseline noise and motion artifact [138]. However, recent development in textile electrode enables the EMG electrodes to enhance user's sweat to increase conductivity and eliminate the need for such preparation. Also, the soft texture of textile electrodes offers a more comfortable alternative to bulky, rigid metal electrodes, making it suitable for an extended use. Fabric-based electrodes produce a flexible interface that can easily be implemented into a compressive sleeve. These factors ensure secure electrode-to-skin contacts and diminish movement in sensor position, offering minimal disturbance in signal quality.

Conventional smart garments are in the form of tight fitting shirts or vests [139]. However, it is cumbersome to fully undress before and after wearing the device. In stroke rehabilitation, where dedication is a critical factor, it is important to avoid anything that may discourage patients from consistent use. An arm sleeve design allows less time and hassle for patients to initiate the therapy. The ease of donning/ doffing and ability to cover the device with outer clothing makes the arm sleeve a great low-profile design for home use.

Repetitive feedback positively influences patient compliance and is associated with improved training outcome. Extrinsic feedback during training is known to support motor learning for stroke survivors, as it compensates for the impaired intrinsic feedback mechanisms [103], [104]. Therefore, it is evident that feedback is a critical factor required for effective stroke rehabilitation. To make the feedback system efficient and productive for elderly [12], it is crucial to develop feedback system simple to understand.

A.5 Smart Sleeve Initial Prototype

The development of Smart Sleeve prototype has not yet been accomplished, however, the list of the design components is addressed in this section.

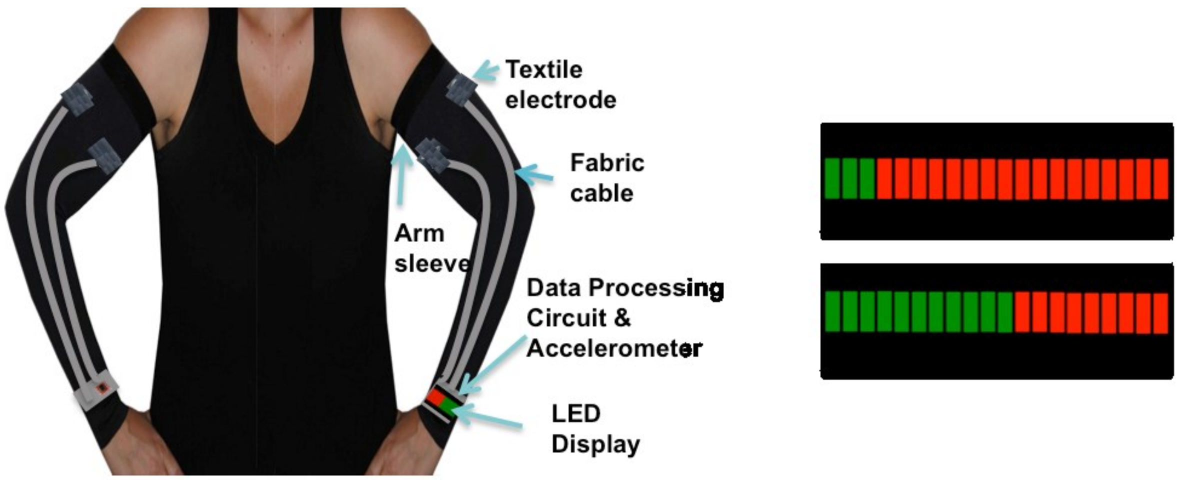

Figure A.1: A concept image of Smart Sleeve interface with the four major components: 1) tri-axial accelerometers, 2) textile EMG electrodes, 3) signal processing circuitries, and 4) visual feedback interface. These four components will be integrated into a compressive sleeve, with EMG sensors placed on the upper arm to monitor muscle activity. In use, Smart Sleeve will be worn on the left and right arms to record activity in both affected and healthy limbs. Wireless communication between the two sleeves will facilitate the calculation of the ratio of activity between the two arms. A simple LED display (shown on the right) on the sleeve will provide a visual representation of this activity ratio. The green color represents the affected arm usage while red color represents the healthy arm usage. Expected arm use ratio at the beginning of Smart Sleeve use is shown on top, and after 6 weeks of Smart Sleeve use is shown below.

A.5.1 Equipment and Components

For each sleeve, the following components will be embedded to monitor and calculate the arm use ratio (Figure A.1). Two electrodes will be embedded inside a compressive sleeve with double-layered backing to maintain its low-profile. Initial prototype will use compressive, tacky material, such as silicone rubber, around the electrode borders to maintain good contact with the skin. The signal processing circuitry will include a 4-channel Analog Front-End chip and a 32-bit microcontroller with necessary input/output ports. The entire circuitry will be contained in a flexible rubber housing, allowing a bracelet-like snap on configuration. In addition, the board will be modified for easy detaching/reattaching to the sleeve as needed to wash the sleeve or to load the data to the PC. One tri-axial digital accelerometer will be used to monitor motion of each arm throughout the day. The micro -ccelerometers will be embedded in each sleeve's processing circuit board for easy installation and usage.

A.5.2 Feedback Mechanism

The motion detection from accelerometer will be the main source of activity monitoring. The front-end amplification circuit on the sleeve of healthy arm will send data wirelessly to the one attached to the affected side via Bluetooth. In order to eliminate unintended movement, recorded EMG signals will be high-pass filtered with a set threshold, defined by user's 20% Maximum Voluntary Contraction (MVC.) The timesteps that do not contain filtered EMG signals will be considered unintended movement and discarded after gathering activity levels from accelerometer data of corresponding side. Then, it will output the ratio of affected to healthy arm usage in a light-emitting diode (LED) display.

The feedback will be presented in two forms, LED display snapped onto Smart Sleeve of the affected limb and a Graphical User Interface (GUI) on the PC. The LED bars will be scaled to demonstrate the ratio "1." The green-colored section corresponds to the affected limb usage while the rest of the section corresponds to the healthy limb usage. This mechanism is chosen instead of numerical display for immediate, easy comprehension in consideration of stroke survivor demographic. The PC-based GUI will enable access to additional information such as absolute arm usage, the intensity of arm usage reflected by EMG signals, and the historical trend of patients' progress. Using this PC-based GUI, clinicians can obtain more objective information about patients' performance and compliance outside of clinic.

A.6 Design Improvement for the Future

Smart Sleeve's simplistic design has a great potentials to enhance stroke rehabilitation when developed further. First of all, donning and doffing of the sleeve on healthy limb requires the use of the affected limb. The compressive material of the sleeve should make it easy to roll on the sleeve, however, using a Velcro closure can make the process effortless. Also, smartphone application will be a convenient tool to display feedback and progress in an understated way. It allows easy portability, immediate access, and user-friendly display, making it an attractive alternative to a PC-based interface. With smartphone application, the alarm function can serve as a reminder for patients to either initiate their exercise for the day or observe there are use ratio thus far to check their progress. This will give patients a sense of challenge, resulting in a motivational boost and increased hours spent using their affected limb.

Also, integrating an additional accelerometer or inertial measurement unit (IMU) close to humerus will allow calculating a trajectory of the affected limb movement, which provides detailed and quantitative information regarding patients' improvement. Another application of this kinematic tracking is the rehabilitation games in virtual environment. There has been a rapid development in Microsoft Kinect-based games for motor rehabilitation [128], however, the limitation lies in its lack of sensing muscle contraction. The user's trajectory and muscle activation on the affected limb can be converted to input of simple game environments, so that dynamic functional exercise can be performed in a fun and jovial environment. Patients will be able to engage family members or friends to play the rehabilitation game together, which in turn increases patient's motivation and triggers sense of challenge.

Another potential improvement of design is in the length of sleeve. Current design demands wired connection between EMG electrodes and the processing circuit. By connecting EMG electrodes to a flexible, small-framed circuit that has micro-sized Bluetooth transmitter to send EMG signals to the main signal processing circuit, the length of sleeve can be cut to just cover humerus. Consequently, stroke patients have more wardrobe options for outdoor activities without sacrificing its discreet characteristic. However, it will require a considerable amount of time to find the suitable components capable of this function without compromising comfort and its low-profile design. Moreover, the muscle contraction can be measured from forearm to encourage more distal portion of the limb movements. By altering electrode-sleeve contact to snap-on button connection, patients can move the electrodes to extensor and flexor of forearm as sufficient motor recovery is achieved in proximal part of the limb.

A.7 Conclusion

APPENDIX: UPPER LIMB STROKE REHABILITATION

Smart Sleeve is designed to motivate stroke patients to increase the use of their affected limb during the course of everyday activities. Using EMG/accelerometer hybrid sensor, Smart Sleeve can provide more accurate measure of patients' activity level. Simple LED display presents an immediate feedback of affected to healthy arm use ratio. Moreover, its ability to log the data enables clinicians to obtain objective, quantitative information regarding patients' progress, which leads to effective, evidence-based treatment regime.

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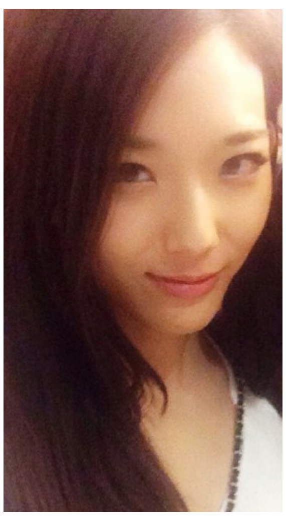
Vita

Inhwa (Tina) Lee was born in Yeosu, South Korea in February 18th 1989. She moved to Irvine, California to pursue a better education at the age of 15 and graduated from Beckman High School in 2007. Tina then entered The Johns Hopkins University and received a Bachelor of Science degree in Biomedical Engineering with a concentration in Instrumentation in 2011.



Upon completing an internship at Infinite Biomedical Technologies, Tina was accepted into the Biomedical Engineering Master's program at The Johns Hopkins University to further pursue her passion in motor rehabilitation. She served as a teaching assistant in Biomedical Sensors and Instrumentation during the Spring of 2013 as well as in Principles of Design of Biomedical Engineering Instrumentation throughout the Fall of 2013.