Desktop Training and Evaluation of Upper Limb Myoelectric Control Strategies

by

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Abstract

The adoption of powered myoelectric prostheses and their ability to improve quality of life for persons with amputations is hindered by the difficulty of controlling multiple degrees of freedom with a limited number of input signals. Different myoelectric control strategies have been developed to address this challenge, but research evaluating myoelectric control strategies in a wearable prosthesis with actual prosthesis users is limited. Performance using myoelectric prostheses is significantly impacted by user training with the selected control strategy; however, minimal research has been done into the effect of functional user training with different myoelectric control strategies, as this typically requires training and evaluating prosthesis users with differing device configurations and customized socket fittings. Desktop-mounted robotic devices offer a potential intermediate platform for myoelectric control training and evaluation of participants with less intensive requirements than a full socket fitting, but more applicability to functional prosthetic ability than offline or virtual evaluations.

In this thesis work, a training environment and protocol for improving myoelectric prosthetic control with a desktop-mounted robotic arm was developed and assessed with pattern recognition as the control method, and a novel evaluation of myoelectric control using the desktop-mounted robotic arm was developed and assessed for test validity. Pre-training and post-training performance for 10 able-bodied participants was evaluated using the Target Achievement Control (TAC) test for 1, 2 and 3 degrees of freedom. Post-training performance was also evaluated in two successive blocks with a novel evaluation task, the Cup Deposition test, using the desktop-mounted robotic arm. Results on the TAC test showed significant differences in performance before and after 1 hour of desktop training, supporting the hypothesis that a desktop training protocol may improve performance with pattern recognition-based control. Results for the Cup Deposition test indicated good test-retest reliability and concurrent validity with the TAC test for research purposes.

Preface

This thesis contains information from one conference paper, authored by the writer, accepted for an upcoming conference at the time of publication of this thesis.

1. J. A. Austin, A. W. Shehata, M. R. Dawson, J. C. Carey, and J. S. Hebert. “Improving Performance of Pattern Recognition-based Myoelectric Control using a Desktop Robotic Arm Training Tool,” in *IEEE Life Sciences Conference (LSC) 2018*, Montreal, Canada. Accepted as of August 23, 2018.

For the study presented in this conference paper, the writer led the planning, data collection, analysis of the data, and writing of the majority of the manuscript; the writing of the discussion section and the revising of the manuscript was shared. The contents of this conference paper are integrated into Chapter 4 of this thesis.

Approval for the studies within this thesis was obtained from the University of Alberta Health Research Ethics Board, “Evaluation of Advanced Control Strategies” (Pro00079472), and all participants provided written informed consent.

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1.0 Introduction

1.1 Problem Statement

Myoelectric prostheses with multiple degrees of freedom (DoF) are difficult to control due to a limited number of input signals [1][2]. This limitation can make them slower and less intuitive to use, hence discouraging widespread adoption and limiting their ability to improve quality of life for persons with amputations [3][4]. Different myoelectric control strategies aim to address these issues, including conventional direct control and pattern recognition-based control [1][5]. However, it is difficult to know how successful these strategies are, because they are rarely evaluated in a wearable prosthesis during functional tasks performed by actual prosthesis users. Such experiments typically involve few participants and high-burden intervention including custom-fitting of a prosthesis, training, regular use and testing. For these reasons, most assessment relies primarily on offline evaluations and virtual reality-based tests, and to some extent, on evaluation tasks performed by able-bodied users with a wearable prosthetic-bypass device that simulates a prosthesis, or using desktop-mounted robotic arms. Additionally, despite its importance to rehabilitation and potential impact on performance, the effect of user training with differing myoelectric strategies has seen only limited investigation and assessment with functional task evaluations relevant to clinical outcomes [6][7].

Desktop-mounted robotic devices can be used as an intermediate research and training platform for prosthetic control [8][9] with numerous potential benefits. There are no socket fitting or mounting requirements, thereby reducing the set-up requirements and confounding factors typically involved in testing [5]. These devices can be used by both able-bodied individuals and individuals with amputation, and the set-up can provide quantitative data on the performance of control systems on simple functional tasks in a consistent test environment. However, the validity and correlation of control strategy performance measures taken using platforms other than socket-mounted wearable prostheses have only minimally been studied, rendering it difficult to meaningfully incorporate these intermediate platforms into myoelectric control strategy design, training protocols, or selection for users.

1.2 Motivating Questions

The broad high-level questions motivating the research presented in this thesis can be summarized as follows:

1. Can we meaningfully evaluate and compare the functionality of different myoelectric control strategies for upper limb prosthetic devices through assessments of performance made using tasks performed on desktop-mounted devices?
2. How does myoelectric control training completed on desktop-mounted devices translate to improvements in performance measured on other platforms, ranging from virtual reality environments to wearable prostheses?

1.3 Specific Objectives

In order to begin addressing the motivating questions described above, the objectives that must be met that fall within the scope of this thesis are as follows:

- To complete the technical development of a configuration for controlling a desktop-mounted robotic arm with pattern recognition-based myoelectric control.
- To develop a protocol and standardized task set-up for training and evaluating myoelectric control with a desktop-mounted robotic arm.
- To assess the effect of the desktop training protocol on myoelectric control performance on a previously established virtual evaluation task, and to assess the validity of the desktop evaluation task, by conducting an experimental study with able-bodied participants.

1.4 Thesis Outline

In Chapter 2, a general background discussion of upper limb prosthetic myoelectric control strategies is provided with a review of literature in the field, including details of different control strategies, current state of research and goals in this area, comparisons between strategies, methods of evaluation and platforms for testing, areas for improvement and gaps in the literature, and proposed training protocols.

In Chapter 3, the equipment used in this study and the technical development required are outlined, including rationale for selection of equipment, design methodology and changes implemented to existing software; the development of the desktop training protocol and the novel desktop control evaluation task is also described.

In Chapter 4, the implementation of the experimental study and the results produced are described in detail. This includes the description of the experiment structure and protocol, a summary of the data collected, the statistical analyses applied, and the presentation of the results alongside interpretation of results and discussion in the context of the existing literature and the objectives of the thesis, as well as the limitations of the study.

In Chapter 5, conclusions of the study and its broader impact are presented, as well as recommendations and proposals for further work in the field building upon this thesis.

2.0 Background Literature Review

2.1 Introduction

Through injury, disease or other means, a great number of people worldwide find themselves without use of one or both of their arms due to amputation; in the United States alone, an estimated 541,000 people were living with upper limb loss in 2005, with 41,000 of those having major upper limb loss (amputation proximal to the wrist) [10]. Incidence of upper limb amputation has been estimated at over 5 in 100,000 US population each year, or 1 in 200,000 for major amputations [11]; approximately 75% of upper limb amputations have been related to traumatic injury [12]. For individuals with upper limb amputations, prosthetic limbs have the potential to drastically improve quality of life. In particular, powered upper limb prostheses have made significant advances in complexity and capability, to the point of being able to replicate nearly all the degrees of freedom (DoF) of a natural human arm [13][14]. The most common method to control these prosthetic devices is by reading, measuring, and interpreting electromyographical (EMG) signals from muscles in the user's residual limb, termed **myoelectric control**; this form of control is appealing for its potential to restore relatively intuitive, natural, unencumbered movement to a person with an amputation [2].

However, these advanced powered prostheses do not always see widespread adoption, with up to 39% of patients rejecting myoelectric prostheses after trying them [15]. A long-term survey by Wright et al. at one clinic indicated only one in four persons with upper limb amputations chose to use myoelectric-controlled prostheses [16], and a more recent survey by Kyberd et al. in 2011 indicated only 23% use in Europe and Canada [17]. In a survey administered by Biddiss et al., 68% of non-users expressed that they were willing to reconsider prosthesis use if improvements in the technology were made at a reasonable cost, including increased dexterity and fine motor skills and improved control and movement of joints [4]; similarly, other surveys have identified design priorities for myoelectric prosthetic devices as including wrist movement and individual finger movement [3] and increased dexterity through more controllable degrees of freedom [18].

One difficulty with advanced myoelectric prostheses is that with increased DoFs come increased control system requirements, yet the number of input signals discernible through myoelectric control is typically limited [1][2][19]. While surgical developments such as targeted muscle reinnervation [20][21][22] can increase the number of available myoelectric input signals, this remains a strongly limiting factor in the control of complex prostheses with many degrees of freedom. Nonetheless, various recent technical developments and approaches to myoelectric control show promise towards increasing

ease of use and efficiency, such as advances in signal processing and analysis of EMG input signals [1][5], methods to improve robustness and consistency of signals over time [23][24], and incorporation of real-time prediction and analysis algorithms that adapt to the user [25][26]. The following is a summary of upper limb prosthetic myoelectric control strategies, including details of both conventional myoelectric control and pattern recognition, comparisons between strategies, recent advances and developments, methods of evaluation, and proposed training protocols.

2.2 Conventional Myoelectric Control

Conventional myoelectric control (CMC) consists of measuring the muscle activity in either one muscle or two antagonist muscles and actuating a corresponding prosthesis joint movement once the muscle activity surpasses a certain threshold. This is a well-established control method that has been applied in a number of commercial prosthetic devices [14]. With CMC, the number of myoelectric input signals is limited by the number of appropriate distinct muscle sites available for EMG measurement. Though surgical developments such as targeted muscle reinnervation have increased the potential number of myoelectric input signal sites [27][28], when compared to advanced complex upper limb prosthetic devices with many actuated degrees of freedom (DoF), the number of DoFs that can actually be controlled via CMC is still very limited. Additional DoFs can effectively be added by using a toggle signal to cycle through different joints being the actively controlled DoF [29], but this tends to be slow, unintuitive and unreliable [19]. This system can also be used to toggle through a list of different grasp types. Various schemes have been proposed to navigate this list more quickly and efficiently, such as event-driven finite-state algorithms, postural domain controllers [30], or an array selection technique for grip parameters [31], but these still require an unintuitive toggling action by the user. In addition to a lack of available muscle groups for input signals, because it only measures EMG magnitude and no other features that could improve its ability to distinguish between signals, conventional myoelectric control faces issues due to its limited sampling depth and the effect of cross-talk between muscles [5].

2.3 Pattern Recognition

An alternative means of myoelectric control that has seen much work in past decades is pattern recognition [5][32]. Pattern recognition (PR) allows multiple DoFs to be controlled even with a limited number of muscle sites and myoelectric input signals. For pattern recognition, raw EMG data is taken from a number of electrodes placed on the remaining musculature and/or reinnervated muscles of the user. The number of channels and electrodes used depends on the system; it has been established that four to five is typically sufficient for transradial users (four channels enabled upwards of 95% offline

classification accuracy across 10 different motion classes) [5], though more are frequently used to maximize classification accuracy, especially with targeted muscle reinnervation [28]. After filtering and pre-processing, the EMG signal is segmented, and meaningful features are extracted across each segment; studies with transradial prosthesis control have established that the optimal window length is generally 150-250 ms [33].

There are a wide variety of possible signal features that have been used for pattern recognition, including simple time-domain based measurements such as mean absolute value, variance, and number of zero-crossings; features from short-time frequency transform, wavelet transform and wavelet packet transform; and autoregressive and cepstral modeling coefficients [5][34]. Reviews and multi-data set comparisons have concluded that, while combining features can increase classification accuracy and stability [35], for most pattern recognition purposes, simple time-domain features, either with auto-regressive coefficients or alone, are generally sufficient and most effective for the computation required [5][35][36][37]. The features can also be reduced in dimensionality either by selecting only a subset, or by using techniques such as Principal Component Analysis, Independent Components Analysis, or Nonlinear Projection to transform them to a smaller dimension feature space [5]. The features of the EMG signals are then used to train a classifier algorithm. Many different types of classifier have been developed and tested, including Linear Discriminant Analysis, Support Vector Machines, Artificial Neural Networks, hidden Markov Models, and Multi-Layer Perceptron. However, experimental comparison by Hargrove et al. has indicated most classifiers perform comparably well [37], hence the simplest and therefore most commonly used are the Linear Discriminant Analysis classifiers [5].

Once the classifier has been trained on the features and however many corresponding classes of motion are desired, it can be used to interpret new EMG data and predict the user's intent, matching it to one of the established motion classes and actuating that prosthetic joint accordingly. Detailed summaries of the current state of pattern recognition algorithms can be found in a number of review papers [5][35][36]. By offline measures, modern PR-based systems are relatively robust; Scheme and Englehart note that offline classification rates regularly exceed 90% accuracy for basic hand/wrist motions for participants with transradial amputations [5], and Kuiken et al. measured 96% classification accuracy for elbow/wrist motions and 87% for grasp patterns for participants with transhumeral amputations in 2009 [28], though these rates decrease for larger numbers of motion classes [36]. A number of pattern recognition software programs and associated training environments are currently available commercially or open source, such as BioPatRec [38], Classifier Evaluator in a Virtual

Environment (CEVEN) [39][40], the CoApt "Complete Control" system (CoApt LLC, Chicago, USA) [41], Infinite Biomedical SENSE controller (Infinite Biomedical Technologies, Baltimore, USA) [42] and Myotrain software [43].

2.4 Pattern Recognition vs. Conventional Myoelectric Control

Pattern recognition has been compared to conventional myoelectric control in a number of contexts and evaluations, including comparison in simulated environments [44][45][46], with able-bodied participants with bypass prostheses on functional tasks [47][48][49], and to a limited extent, with users of wearable prostheses on functional tasks [50][51]. In these comparisons, recent versions of pattern recognition generally demonstrate superior performance to CMC in most contexts. Nevertheless, unlike conventional myoelectric control [14], pattern recognition was unable to transition to commercially viable products until recently [52][53], and even then only to a limited number of prosthetic devices. Reasons for this include technical issues such as signal consistency deteriorating over time, increased training and configuration requirements for users, potentially higher cognitive demand of the user to control more DoFs, and lack of an easily configured user interface for clinicians and patients. Lastly, a relative scarcity of in-depth functional and clinical evaluation leads to uncertainty in the relationship between classification accuracy and prosthesis controllability [14]. Pattern recognition has been implemented in wearable prosthetic devices for several years, often in combination with targeted muscle reinnervation, as shown by Kuiken et al. with the John Hopkins University Applied Physics Lab (JHUAPL) arm and the DEKA arm (DEKA Integrated Solutions Corp., Manchester, USA) [28]. A number of clinical prosthetic devices designed specifically to operate with pattern recognition are currently under development and show promise [54][55]. In general, though, there exists a large gap in translating the promising effects of newer myoelectric control strategies to functional improvements for the users; Jiang et al. note a significant discrepancy between research achievements in the field and the clinical or commercial impact of these developments [52], and Asghari Oskoei et al. note similarly the lack of improvement in application of myoelectric control compared to laboratory-based advances [1].

2.5 Challenges for Pattern Recognition and Current Research

Despite a great deal of work in the field over the past decade, there are still numerous areas in which pattern recognition needs to improve to become more viable for daily use. Broadly, pattern recognition compared to natural physiological control is less intuitive to use: natural control is continuous, proportional and involves coordinating patterns of multiple DoFs simultaneously (also known as synergies [25][56]), whereas basic pattern recognition classification tends to be discrete,

binary and sequential. Recent research, however, is beginning to address this discrepancy. Pattern recognition originally classified only the transient portion of the signal, therefore requiring that discrete motions be initiated from rest in order to be consistently classified. This prohibited intuitive switching between classes, impeding the coordination of complex tasks involving multiple DoFs [57]. In order to move beyond only the transient pattern and process steady-state EMG signals, a "continuous classifier" was developed by Englehart et al. using wavelet analysis [58], and subsequently with time domain features [59]. This has since seen further development and is the standard type of classifier used today [57][60] .

Proportionality, in the context of prostheses, is the ability to control and vary the velocity or force of a prosthesis across an essentially continuous interval [61]. This has been implemented effectively with conventional myoelectric control, even in commercial prosthetic devices, but proves more challenging with pattern recognition. It is either implemented post-classification or by using additional classes for different intensity levels. Post-classification implementation is based solely on EMG mean absolute value levels, ignoring other differences in EMG patterns at different contraction intensities and resulting in reduced classification accuracy at contraction intensities different than the training set [35]. However, using additional classes decreases maximum classification accuracy overall due to the larger number of possible classifier outputs involved [5][36].

Simultaneity is the ability for two or more distinct prosthetic motor functions to be selected for activation concurrently [61]. Simultaneous control has been implemented in simulated tests using classifiers capable of simultaneous prediction such as Multilayer Perceptron classifiers, or various classifier "distributed topologies" that use singular classifiers to compare different combinations of classes [62]. Some novel pattern recognition approaches are under development to try and include simultaneity by reducing dimensionality of pattern recognition features according to muscle synergies, expressing surface EMG patterns as a function of intended activations of natural physiological movements [63]. Currently, both simultaneous and proportional pattern recognition have been implemented with some degree of success in limited DoF systems, and compared to sequential pattern recognition, discrete pattern recognition and conventional myoelectric control using both simulated prostheses [45][62] and on functional tasks with able-bodied participants using bypass prosthetic devices [49].

Another issue that affects the use of pattern recognition is its inability to adapt to varying EMG input conditions in actual use outside the lab. Performance deterioration is influenced by many factors,

including sweating, muscular fatigue, reduction in user focus (resulting in changes in their activation patterns), electrode shift, inadequate socket positioning, and changes in residual limb position or fluctuation of residual limb volume [25]. Training with dynamically varying data can drastically improve robustness [23]; for example, the effect of electrode displacement due to limb position and external loading can be mitigated by using a training set of data recorded from motion over a range of plausible electrode displacement locations [24][64], though this does reduce maximum classification accuracy. However, not all possible patterns can be covered in classifier training, given that user training can take up several days and be very arduous [25]. Surface EMG signals are both time-dependant and user-dependant [26][65], meaning interpretation needs to be both personalized to the user and continuously adaptable to EMG input conditions. Some work has been done on adaptive classifiers that can update with data after the initial training if performance degrades [26]. The classifier training process for individual users can also be boosted by machine learning methods, taking a large set of standard surface EMG training data and weighting it individually per user [65]. Momen et al. have attempted to decrease user fatigue and increase natural ease of use by allowing users to employ whichever arbitrary muscle contractions are most natural, consistent and distinguishable as EMG inputs, rather than using pre-set motions [57].

Lastly, a common issue with PR-based control is false activation of unintended motions, which has been noted as a significant cause of user frustration during functional testing [34]. To mitigate error, pattern recognition can be combined with an output framework beyond simply discrete motion selection. For example, techniques such as multiple binary classification, deciding action selection through majority vote of different classifier/feature combinations, generating confidence scores to accompany class selection [66], and using a velocity ramp to implement the selected action [67], have shown general improvement in both simulations and in simple functional tasks over standalone PR-based control. In general, pattern recognition is anticipated to perform better as a part of larger incorporated dynamic system of myoelectric control [25].

2.6 Real-Time Machine Learning

One element of particular interest for potentially incorporating into a larger dynamic control system, for either pattern recognition-based or conventional myoelectric control, is real-time machine learning. Pilarski et al. note that “contextual or situational awareness is important for improving and adapting myoelectric control systems” [25], especially given that humans already use learned, adaptable predictions to effect timely and appropriate actions with their physiological limbs [25]. The starting

point of the application of real-time machine learning to prosthetic control is the prediction of sensor data, such as user EMG input and prosthetic actuator state [68][69], and the use of this information to anticipate desired user control functions [68] and timing of their behaviour [70]. These predictions can be used to modify control parameters, such as adjusting gains, thresholds and filters, or dynamically re-ordering control options, as illustrated by Pilarski et al. with an adaptive switching algorithm to toggle more efficiently through active DoFs [68]. The predictions can also be used as additional sources of input to a myoelectric control scheme, for example in order to control certain DoFs autonomously without direct user input being required. Autonomous control of active joint selection was demonstrated later by Edwards et al. [71], who developed a system that used off-policy General Value Function learning to make predictions about both what user input would be and when it would occur [70]. In this study, when the system was confident enough about its predictions, it could switch to the predicted desired DoF without user input, with feedback informing the user about the switch. Autonomous switching in combination with adaptive switching and feedback reduced switches per sequence and time per motion, adding more practical utility to adaptive switching [71]. Future work could apply this method to more complex tasks as well as improve its efficacy with further user training. Lastly, real-time machine learning could be applied towards collaborative control strategies between user and machine. Sherstan et al. demonstrated an implementation in which the user could toggle between DoFs to control a single active joint at time, while a Direct Predictive Collaborative Control algorithm controlled the other DoFs using predictions based on training runs, and adapting to current runs [72]. No functional evaluations of myoelectric control involving real-time machine learning have been performed yet with wearable prostheses, but limited tests so far have included both able-bodied participants and participants with amputations controlling a desktop-mounted arm with EMG input [73][74].

2.7 General Goals for Myoelectric Control Improvement

The development of enhanced PR-based myoelectric control systems can be characterized as the pursuit of improvements in the robustness, the adaptability, and the awareness of the whole system [25]; this includes the aforementioned developments to pattern recognition algorithms to allow for simultaneous, continuous, proportional and intuitive control. Recent research has begun to focus on the incorporation of synergies [25][56], i.e. controlling multiple DoFs simultaneously in a coordinated patterns, where the control system enables the user to select variations of useful movement patterns rather than only discrete joint motions [56]. In general, the goal of intelligent myoelectric control systems is to strike a balance between the burden of control on the user and the burden on the software; the latter can make motion faster and more intuitive by delegating more details to the

machine, but can also lead to frustration due to limited prediction accuracy and more intensive software training requirements [25]. This shared control of a prosthesis has been implemented and evaluated to some degree in research such as that by Cipriani et al. [75], in which a multi-DoF prosthetic hand was evaluated with a variety of control hierarchy schemes and degrees of shared control between user and machine. Though more user control theoretically permits more precise motion, in practice less effort and attention is preferred; such a system would therefore also benefit from the availability of sensory feedback to the user [75]. Myoelectric control systems should therefore ideally be able to use limited input signals to control multiple DoFs at once in a coordinated fashion instead of discretely, but without having to manually train the classifier on all possible input patterns and prosthetic motions; the system should be able to adapt to cover these based on minimal training. The need for a more intelligent, informed dynamic system in which pattern recognition can operate ties into other important areas of general research towards the improvement of myoelectric prostheses in general, such as the incorporation of sensory feedback for the user and the integration of sensory modalities into the performance of complex actions [25].

2.8 Evaluation of Myoelectric Control

Aside from areas of technical improvement, several authors such as Jiang et al. note that one important reason for the lack of transition of myoelectric control strategies to clinical and commercial technology is that the research focuses too much on mathematics and mechatronics, and not on the ability of a prosthesis user to use the system in activities of daily living [52][76]. They suggest that systems should not be evaluated purely on abstract classification rate with offline data, as is most commonly done [77], but should incorporate functional measures of performance as well. Ideally this would involve being compared against standard quantitative benchmarks, then assessed in a clinical setup with wearable prostheses [25]. Both myoelectric control development and evaluation should also integrate clinician input, so that clinicians are satisfied with the tools they are provided, and are better able to help select and train the best control strategy for an individual patient [52].

2.8.1 Offline Evaluations

Most quantitative tests used in research are offline abstract evaluations of classification error rates using pre-recorded data [25]. These are the simplest to implement and are not influenced by complicating factors on functional tests like individual prosthesis capabilities, socket fit, user experience, etc. [5] Classification accuracy is the simplest metric for pattern recognition, assessing the percentage of input signals correctly matched to the motion class intended by the user. It is worth noting that

classification rates alone do not necessarily correlate strongly with usability, as shown by Lock and Englehart [78]; while high classification accuracy can benefit task completion efficacy, certain pattern recognition classifier training strategies can show reduced classification accuracy but increased performance in functional tasks, and vice versa [39][66]. Even within offline measurements, the most commonly used metrics such as global classification accuracy may be biased towards misleadingly high values that neglect the effect of false positives. Instead of global classification accuracy, Ortiz-Catalan et al. advise using class-specific accuracy, well as precision and sensitivity metrics [79].

2.8.2 Online Virtual Tests

The demand for more practically applicable evaluations has led to the development of a number of real-time, online quantitative measures. Online classification accuracy uses real-time EMG input data instead of pre-recorded data to select motion classes in real time and compare against the user's intended movements. The Fitts' law test (FLT), or Fitts' law style assessment, requires a user to efficiently and precisely move a cursor to a random target, and fits the result to the Fitts' law relationship to obtain an Index of Difficulty [46][80]. The Motion Test requires the user to follow prompts to move a simulated limb through a range of motion [28]. The Target Achievement Control (TAC) test requires the user to observe and match the motion of a simulated limb and maintain the target position, allowing assessment of motion speed, efficiency and unintended activations [81]. Most investigations use able-bodied participants in virtual reality environments, for several reasons: it is easier to set up and manipulate the environment, able-bodied participants are more plentiful than participants with amputation, and a relatively "ideal" performance can first be established. Functional evaluations with wearable prostheses are more difficult due to the lack (until recently) of commercial PR-based prosthetic devices [52][53], and the additional technical burden of having to custom make sockets for testing participants with amputation. Therefore, many functional evaluations use bypass prosthetic devices for able-bodied participants instead, or sometimes desktop-mounted robotic arms. Though it is unclear how well the results of functional evaluations with able-bodied participants translate to participants with amputations, a study by Scheme et al. that assessed classification accuracies for both able-bodied participants and participants with transradial amputations indicated slightly lower average performance for the latter, but overall relative performance across various classifiers being similar between the two groups [82].

2.8.3 Functional Prosthetic Tests

A number of simple functional quantitative evaluations are often employed to investigate prosthetic control, including the clothespin relocation test, Box and Blocks test, and box-stacking test; for example, these tests were used in a comparison of conventional myoelectric control to PR-based control by Hargrove and Levi at the Research Institute of Chicago [51]. The use of objective quantitative measures and simple, highly standardized activity set-ups make these types of tests favourable for comparison of basic function in a research and development context [83]. These tests can also be refined or modified for more specific purposes, such as the refined clothespin relocation test [84], which constrains motions to standardize for comparisons and better identify compensatory motions, or clothespin relocation with periodically disabled electrodes for comparison of pattern recognition performance after different recalibration methods [85]. Additional data for analysis can be extracted from these tests using tools such as Motion-Capture [84][86]. The practical functionality of a control scheme is also dependant on how much attention is required to perform a task [30], which is another reason for the popularity of simple one or two DoF conventional myoelectric control prostheses over PR-based control. Therefore, evaluations have also been performed that attempt to measure and compare cognitive load or user focus, using techniques such as electroencephalography [87], gaze tracking [48], and pupillometry [47].

There exist a number of observer-rated clinical functional tests that can be used for evaluation of prosthetic hand and arm control, in which assessment is based on a clinician's observations of the participant performing various activities. Determining which tests are most appropriate in which contexts, however, is an ongoing discussion and recommendations are still under development [83][88]. As these tests are activity-based, they can be useful for assessing both basic control functionality and applicability to tasks of daily living [83]. A notably popular test is the Assessment of Capacity for Myoelectric Control (ACMC), in which 30 items (various parameters of simple motions) grouped into 4 categories (gripping, holding, releasing and co-ordinating) are rated on a 4-point scale, assessed through various two-handed tasks chosen by the therapist and the user [89]. This test can be applied to myoelectric prostheses for any level of amputation; however, certification is required for its application, and it is fairly labour-intensive [88]. Another common test is the Southampton Hand Assessment Procedure (SHAP): a clinically validated test of hand function consisting of manipulations on both abstract objects, and activities of daily living [90]. Other functional tests include the Prosthetic Upper Extremity Functional Index (PUEFI) and Assisting Hand Assessment (AHA), though these are traditionally pediatric and need to be validated with adults [88]; and the Jebsen Taylor and Sollerman tests, though these need to be validated to apply to prostheses users [88][91]. In their systemic review of outcome

measures in 2017, Resnik et al. rate a number of tests on how well their psychometric properties have been established [92]. Their top four suggestions for clinical functional tests are the Activities Measure for Upper Limb Amputees (AMULA), a test similar to ACMC in which 18 items for household and self-care tasks are scored by an evaluator on a 4-point scale on sub-elements of task completion, speed, movement quality, prosthetic skill, and independence; the University of New Brunswick Test of Prosthetic Function (UNB), in which the performance of the user on various tasks is assessed by an evaluator on scales of both spontaneity and skill; the Box and Blocks test; and a specific subtask of Jebsen Taylor Hand Function test involving lifting and moving cans.

2.8.4 Self-Reported Measures

Lastly, prosthetic control can be evaluated through self-reported assessments. This includes measures such as the Disabilities of the Arm, Shoulder and Hand (DASH), the Hand Assessment Tool (HAT) [92], the Trinity Amputation and Prosthesis Experience Scales (TAPES) [93], and especially for upper limb prosthetic devices, The Orthotics and Prosthetics User Survey Upper Extremity Functional Status (OPUS-UEFS). These assessments, known as participation measures, allow the participant to indicate how well the prosthetic device is integrated into daily tasks during use at home [83]. These are therefore best suited to take-home trials or long-term assessment of commercial prosthetic devices.

2.9 Application of Evaluation Methods

The evaluation of myoelectric control strategies can also be broadly categorized according to the platform on which they are implemented. These platforms include 1) simulations, including offline data evaluation, simple online cursor-control tasks, and tests in virtual reality environments (VRE); 2) desktop devices, meaning stationary robotic manipulators not worn by the participant; and 3) wearable devices, including both regular socket-fitted prostheses for persons with amputations, and wearable bypass-prosthesis devices (sometimes known as prostheses simulators) for testing with able-bodied participants. In both research and clinical situations, these platforms are utilized to varying extents in different contexts depending on their advantages and disadvantages.

For simulation platforms, classification accuracy (both offline and online) is the most common metric used for pattern recognition-based myoelectric control strategies. Classification accuracy has been compared against more complex simulated tests [81][78] and against functional task evaluations using wearable prosthesis in a few studies [78][76][94]. Despite not showing strong correlation with these evaluations, it continues to be one of the simplest and most straightforward assessments to apply initially. For both PR-based and non-PR-based control, efficiency and precision can be assessed with simple graphical tests such as the Fitts' law test for up to three DoFs at a time [46][80].

Simple VRE-based tests, which replicate visually the intended motion of the limb being controlled but do not involve interacting with any objects, are a common evaluation tool – the Target Achievement Control test is an oft-used example of this [81]. More complex VRE's that allow object-interaction have been developed and are used to some extent, such as CEVEN Virtual Environment [78], or the VREs developed by Hauschild et al. [95], Lambrecht et al. [96], and Bunderson [97]. Their application to functional tasks has been minimal; simplified simulated versions of reach-and-grasp [95], Box and Blocks [96][97], and clothespin relocation [78] have been performed. Generally, no daily-living activity-based clinical assessments are performed on simulation platforms due to the complexity of modeling these activities and the range of factors (object and prosthesis weight, haptic feedback, effect of socket fit and position) that would necessarily be excluded.

Desktop platforms are used minimally in myoelectric control strategy evaluation, though they do offer many of the advantages of wearable prosthesis testing while negating the need for socket fitting or personalization of the device, and are employed in PR-based training protocols for this reason [8]. Desktop-based devices have been used to perform simple functional task-based evaluations including simplified reach-and-grasp [98] and Box and Blocks [69][99]. They are, by definition, limited to tasks that

do not require user motion above the level of humeral rotation, which also means the compensatory shoulder movements prosthesis users often employ [48][84] are not able to be assessed through a desktop-based evaluation, nor can these movements be used to substitute wrist rotation or wrist flexion if the task requires it. This also renders desktop platforms inappropriate for more complex assessments based on activities of daily living that involve bimanual tasks or presume a participant with a full-body range of motion [89]. Nevertheless, desktop platforms could still feasibly be applied to other myoelectric control evaluations based on functional tasks that involve simple repetitive movement, such as box-stacking, clothespin relocation, carton pouring, and can-moving. They can also be used to physically replicate the visual component of VRE-based simulation tests such as the TAC test, the Motion Test, or similar tests assessing performance of individual motions [71].

Finally, evaluations on wearable platforms are the most challenging to implement, but also replicate actual use of a prosthetic device most closely, making them the most potentially informative as to how well a given myoelectric control strategy will work for a prosthesis user in day-to-day life [5]. Given the comparably greater availability of able-bodied participants, the use of bypass-prostheses for assessment of myoelectric control on simple functional tasks is quite common [47][48][49]; the majority of these replicate trans-radial rather than trans-humeral prosthetic devices, due to the practical challenges involved in effectively mounting bypass-prostheses at higher levels.

Evaluations performed using wearable devices span a wide range, from simple objective functional tasks like Box and Blocks and clothespin relocation, to complex observer-rated evaluations such as AMULA and ACMC; these broader tests, intended to encompass activities of daily living, are generally applied with actual prosthesis users rather than using bypass-prostheses. Since conventional direct control prostheses have been commercially available for decades [14], these tests have all been applied extensively to prosthetic devices with this type of control strategy. In contrast, as prosthetic devices using PR-based control have only recently achieved sufficient reliability for commercial viability [52][53], the evaluation of pattern recognition in wearable device platforms has not been as extensive, but it has increased substantially in recent years as interest in such control strategies expands [51][94].

2.10 User Training for Pattern Recognition-Based Myoelectric Control

User training describes how the wearer of a myoelectric prosthesis learns and practices how to efficiently and naturally use the device, as distinct from the **classifier training** of the pattern recognition system itself using EMG signal features. An understanding of the impact of user training is important for moving towards clinical use and especially take-home or commercial use in the long term. Although

acknowledged to generally involve more user training than CMC [25], the amount of user training required by pattern recognition depends on the complexity of the prosthetic device and of the control scheme, the number of motion classes, the experience of the user, and the level of functionality desired. As a result, there is no standardized training period, only recommended timespans and protocols for initial clinical training. Some research has suggested that maximally efficient use of commercial multifunction prosthetic hands can take up to 1-4 months of daily training [14]. User training has generally not been studied in detail aside from various individual case-studies, though Powell et al. did complete a two-week longitudinal study of the effect of user training on performance with a simulated PR-based prosthesis [7] using classification accuracy and simple Motion Test results as the comparison metric, and Dawson et al. performed a review of various different types of user-training platforms available [6].

User training for use of pattern recognition varies widely, but protocol suggestions have been made. The protocol developed at the Research Institute of Chicago by Simon et al. [8] and similar work by Powell [100] and Stubblefield [101] consists of stages of conceptual training, control training, and functional use training. Initially, users are introduced to the concept of myoelectric control and pattern recognition, as well as relevant vocabulary and definitions [8][100]. Demonstrations can be given in the form of an EMG signal viewer, having an instructor demonstrate use of pattern recognition, then allowing the user to try it themselves using Screen-Guided Training (SGT) for calibration, and control of a simulated prosthesis in virtual reality, or of a desktop-mounted robotic arm [8]. The prosthetist helps them decide and establish which contractions will be used for control, and the users are advised on general tips for successful PR-based control: performing only one movement at a time, ensuring movements are consistent and moderate in intensity, and attempting to move the phantom limb or to mimic the intact limb doing so. Lastly, an initial assessment is conducted to develop plan for further simulated training until the wearable prosthesis is reading for fitting [100]; this can include training at home, which optimizes learning in frequent short sessions, using a prosthesis in VR or playing games to improve myoelectric control in general [100].

Control training develops basic control of a wearable prosthesis with pattern recognition [8]. The user starts with training and controlling the easiest motions in neutral or supported position, then retraining these motions in different displacement locations (various limb positions and load levels) [100]. Once confident with control of these motions, they can move on to more difficult ones. Training should be focused first on improving consistency for each motion, then on improving distinguishability;

this can be done by emphasizing the motion in isolation, than exploring to find which extraneous motions give the best distinguishability [100]. During the process, it is important to reiterate control tips, take breaks, and recalibrate as needed. Recalibration can be performed either with the clinician's instructions, with Screen-Guided Training, or with Prosthesis-Guided Training (PGT), in which the prosthesis cycles independently through motions and the patient matches these autonomous motions with corresponding muscle contractions, allowing for self-recalibration [85][102].

Finally, functional use training improves the use of the prosthesis for tasks of daily living, such as handling objects, grasping and changing their orientation [8]. Once confident with single-handed tasks, the user can subsequently practice bimanual tasks such as carrying larger objects, folding clothes, etc. Beyond this, they can move on to practicing more complex bimanual tasks with higher cognitive demands [101]. During this process, it is important to encourage the use of new DoFs, and again, to reiterate pattern recognition control tips, take breaks, and recalibrate as needed. It can also be beneficial to use videotapes of previous task attempts to illustrate both progress and areas for improvement [101]. The user can also practice self-calibration through SGT and PGT when needed in order to deal with signal deterioration and retain the long-term level of performance needed for functional daily use [8]. At this stage, prosthetic function can be assessed using an activity-based evaluation such as SHAP or ACMC [101]. Beyond this point, the prosthesis user is theoretically prepared to begin take-home trials of the pattern recognition-based myoelectric controlled prosthesis for use in activities of daily living.

2.11 Background Literature Review Conclusions

Though they face a number of challenges, after decades of research PR-based myoelectric control systems have become quite sophisticated, and continue to develop and evolve in new ways, enabling proportional and simultaneous actuation, and generally improving in terms of robustness and adaptability. Part of this evolution involves incorporating pattern recognition classifiers as part of a larger dynamic and adaptable interaction between user and machine. However, transition to commercial products has only recently become viable, and generally the focus of research has been insufficiently directed towards end user application. Perspective has begun to shift, with a greater emphasis on establishing practical functionality, clinician involvement, and development of initial pattern recognition user training protocols. Comparison trials of pattern recognition to other myoelectric control strategies in wearable prostheses using functional tasks are limited, as there are numerous challenges involved in doing so. Though further work is needed to determine the optimal details, an overall evaluation approach for PR-based control and myoelectric control strategies in general could consist of a basic proof of function, such as the TAC test on a simulation or desktop-mounted robotic device; simple functional tests such as Box and Blocks or clothespin relocation, with a prosthesis in either desktop-mounted or socket-mounted wearable configuration, both before and after user training; and finally, activity-based evaluation such as ACMC or AMULA after user-training and familiarization with the prosthetic device.

3.0 Technical Development

For a study investigating the evaluation of myoelectric control strategies for upper limb prostheses, a number of technical components are required, including a means of acquiring myoelectric input signal, a means of processing it, and translation of this information to an output device in such a way that control can be evaluated. While this type of set-up can be implemented in a broad variety of ways with different components, the focus of this thesis on desktop-mounted robotic devices as an intermediate platform and the objectives formulated accordingly in section 1.3 led to the emergence of six specific technical requirements for this project:

1. A powered desk-mounted robotic arm, minimum 4 degrees of freedom (up to 3-DoF controlled myoelectrically, plus shoulder rotation for horizontal positioning of the end effector)
2. Control software for the powered robotic arm
3. Myoelectric pattern recognition implementation software
4. An EMG acquisition system
5. A desktop test environment for training and evaluating control of the prosthetic limb
6. An alternative (non-desktop) control evaluation method for comparison

A system flow diagram connecting the proposed technical components is shown in Figure 3-1. This chapter describes the details of each component selected, the rationale behind the choice, and the design and implementation of any additional technical development needed to modify or integrate it into the overall technical set-up for the experimental study.

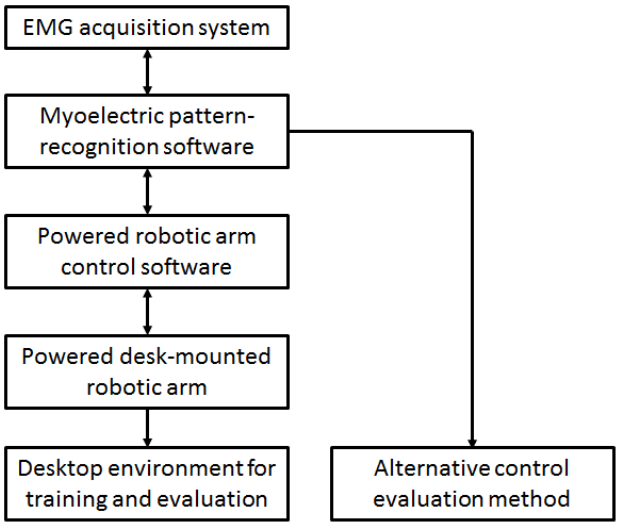

Figure 3-1: Technical Component System Flow Diagram

3.1 Bento Arm

Desktop training in this study was performed using the Bento Arm, a modular open-source robotic platform developed by the Bionic Limbs for Improved Natural Control (BLINC) laboratory, primarily for training and assessing persons with upper limb amputations in the application of myoelectric control prior to being fit with a socket-mounted commercial myoelectric prosthesis [6][9][103]. The Bento Arm, shown in Figure 3-2, consists of an anthropomorphic robotic manipulator (modeled after an upper limb) assembled from custom 3D-printed components and off-the-shelf hardware, and powered by MX-series Dynamixel actuators [104]. It includes 5 degrees of freedom, some currently available commercially (hand open/close, wrist supination/pronation, and elbow flexion/extension) and others that may be available in the future (wrist flexion/extension, humeral internal/external rotation).

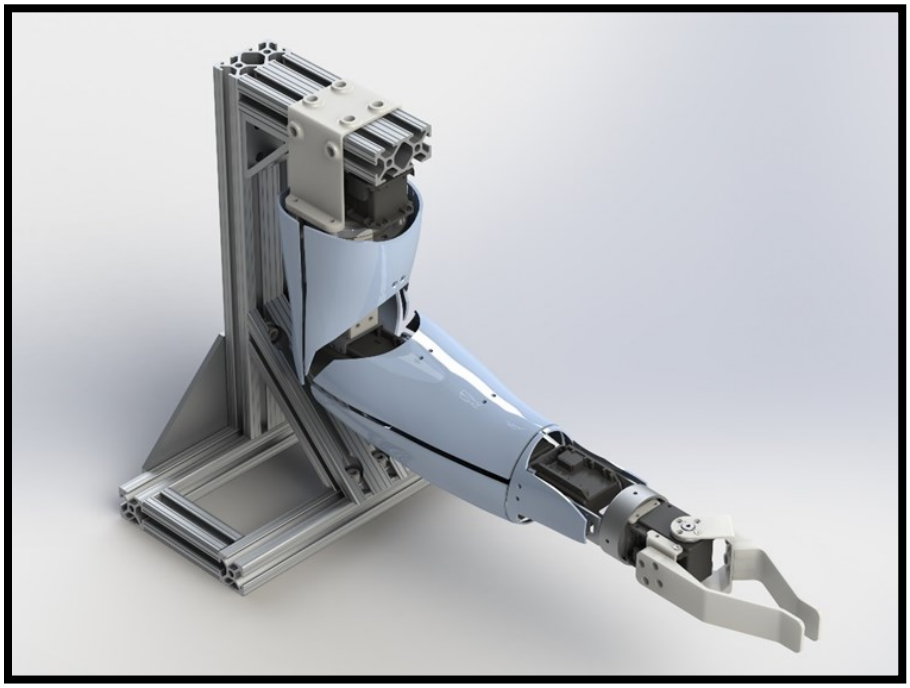

Figure 3-2: The Bento Arm [104]

The Bento Arm was selected for its low cost, its ability to be easily repaired, modified and reconfigured, and its extensive development history in the BLINC lab including numerous future development goals that aligned well with the aims of this project. Furthermore, the Bento Arm is capable of operating in both a desktop-mounted set-up and a wearable socket-mounted configuration, making it an optimal platform for potential extension of this control strategy evaluation research towards users of wearable prostheses [103].

3.2 BrachI/Oplexus

Hardware in the arm was controlled using brachI/Oplexus, an open-source program specifically developed for the Bento Arm that allows for flexible mappings between different input devices (including EMG signals, keyboard and joystick inputs) to the movements of different joints on the robotic arm [105]. Parameters for inputs, joint limits, electrode signal gains and thresholds can be easily customized towards a given experimental set-up or participant in the brachI/Oplexus Graphical User Interface (GUI), shown in Figure 3-3.

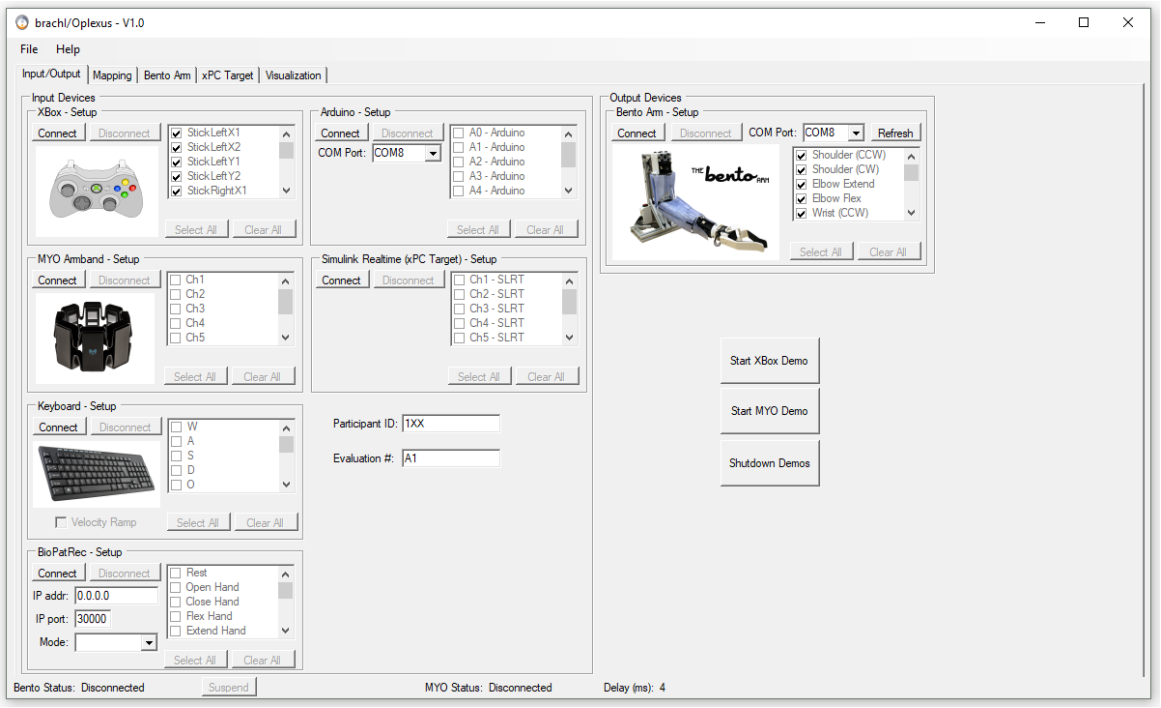

Figure 3-3: BrachI/Oplexus Graphical User Interface [105]

Several modifications were made to brachI/Oplexus specifically for this study, including the addition of button-activated automated movements hardcoded into the brachI/Oplexus code for the desktop evaluation task; load limitations on servos to prevent damage to the arm or test set-up when erroneous motions are made; and an automated logging system, activated either manually or by the start of an evaluation trial, to record both Bento Arm joint position and grip load with a timestamp every brachI/Oplexus cycle. A number of changes were made to render the software compatible with the MATLAB-based pattern recognition software being used, including development of a TCP/IP communications protocol (and corresponding GUI features) to send information such as movement commands back and forth between brachI/Oplexus and external software.

3.3 BioPatRec

Pattern recognition of the myoelectric input signals was applied using BioPatRec, an open-source, modular MATLAB based software developed by Ortiz-Catalan et al. [38]. This software was chosen as it can be easily modified and customized for most devices compared to commercial control systems and maintains open-source status for all software components involved in the desktop system being developed.

Several modifications were made to the open-source BioPatRec code to render it compatible with the other equipment and software being used and to prepare it for the experimental trials being conducted. The motor output functions were modified to send simplified commands (consisting of a movement ID number and a scaled velocity value) to the brachI/Oplexus software through the TCP/IP communication protocol whenever the ID or speed of the active joint changed during real-time pattern recognition. Though a velocity ramp was included in the BioPatRec code, it was originally only incorporated into control in the virtual reality environment; therefore, the pattern recognition code for controlling motors or sending commands to external software was modified to recognize and relay changes in velocity due to the velocity ramp function. Though variable window step incrementation was available in offline calibration using recorded signals, the real-time pattern recognition program defaulted to incrementing by entire window lengths only; the code was therefore also modified to enable windows to be captured and analyzed at any increment from one another.

3.4 Target Achievement Control Test

The alternative myoelectric control evaluation method selected for assessing the effect of the desktop training protocol and for comparison with the desktop evaluation was the Target Achievement Control (TAC) test, a control test developed by Simon et al. [81] that requires the user to control a virtual limb, match it to the position of a simulated target limb and maintain position. This allows assessment of movement selection time, speed, efficiency, overshoot, and unintended activations; other metrics for human-computer interface assessment, such as throughput, can also be derived from TAC results and parameters [106]. Compared to other, simpler virtual tests such as the Fitts' law test or Motion Test, the TAC test captures a wider range of results data and more closely visually approximates control of an actual prosthetic device. It has been applied in several previous studies of myoelectric control to compare direct control and PR-based control [44] or variations of PR-based control [45]. Furthermore it has been correlated with the Fitts' law test, which has been established as an international standard for validation of human computer interfaces [106]. Performance on the TAC test has also been correlated

with performance on the Assessment for Capacity of Myoelectric Control (ACMC), an established clinical evaluation of myoelectric prostheses outcomes [107], supporting the concurrent validity of the TAC test.

The BioPatRec software includes a version of the TAC test already configured to enable evaluation of PR-based myoelectric control; a simulated arm completing a TAC test in the BioPatRec Virtual Reality Environment (VRE) is depicted in Figure 3-4. This code was also modified to render the test compatible with a wide range of input formats and to accept command signals from external programs in order to allow different control systems to be compared on the TAC test. Additionally, the initially limited space tracker functions in the TAC test (used to record movement class selection and resulting VR arm position at every timestep during the test) were expanded to apply to any possible movements being tested, allowing TAC test data to be more comprehensively recorded for validation and post-hoc analysis.

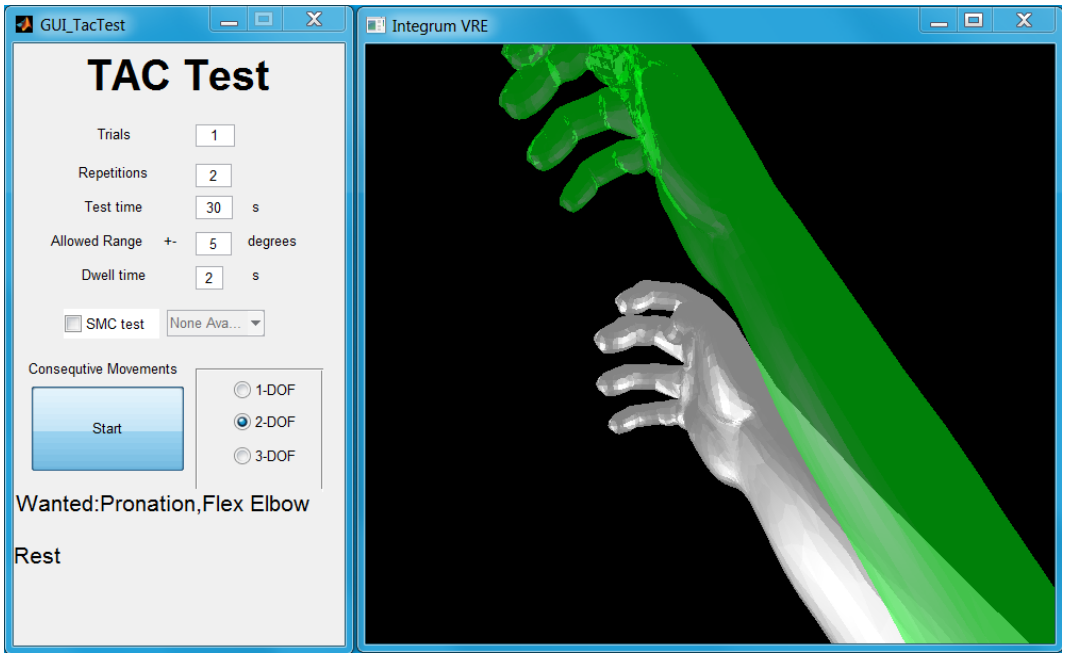

Figure 3-4: The BioPatRec Virtual Reality Environment and Target Achievement Control test

3.5 EMG Acquisition Hardware

The EMG signal acquisition system selected was the Delsys Bagnoli 8-electrode system, due to previous experience using the system, it simplicity, and its compatibility with the BioPatRec software. Up to eight bipolar double differential surface electrodes can be affixed to a participant's skin overtop the muscles of interest, in addition to one reference electrode (ground) placed at a neutral location. When muscle activity is initiated by the participant, the resulting series of action potentials (the physiological electrical activity involved in the contraction of the individual muscle fibers) produces small but

detectable electrical potential differences on the skin surface, spatially and temporally [108]; these are detected and measured by the poles of the electrodes positioned there.

From these measurements, the Bagnoli EMG System produces "conditioned, isolated, analog signals" [109]; specifically, it outputs up to 8 single-ended analog voltage signals in the ± 5 Volt range. The Amplifier unit applies a fixed gain of 1000, raising the initial 0-2000 microvolt measurements to a level comfortably within the desired -5V to +5V analog output voltage range. For the purposes of this research, 6 channels corresponding to 6 electrodes were used, based on preliminary technical validation of the system indicating this yielded the highest classification accuracies for 3-DoF PR-based myoelectric control. Lastly, the Bagnoli-Delsys system connects to a National Instruments (NI) USB-6216 Data Acquisition (DAQ) BNC module, which converts the analog data to a digital signal that is then fed into the MATLAB-based pattern recognition software running on the host computer. Here, it can be recorded for training of the pattern recognition controller, or filtered and processed in real-time to implement PR-based control.

The sampling rate of the Delsys Bagnoli system is 1000 Hz, which according to Nyquist theorem corresponds to the Nyquist sampling rate for a signal of up to 500 Hz in frequency [110]. EMG literature indicates that the majority EMG signals occur between 20 and 500 Hz, with most of the important signals being below 300 Hz [111]; therefore, this sampling rate is sufficient for the anticipated signals. Some level of initial filtering is performed within the Delsys Bagnoli system, as the frequency response of the Bagnoli Amplifier Unit is 20±5 Hz to 450±5 Hz, with higher and lower frequencies being attenuated[109]. The system therefore applies an anti-aliasing filter by excluding signal elements with high-frequency components, i.e. high frequency noise. As the Nyquist frequency for a 1000 Hz sampling rate is 500 Hz, attenuating signals elements above 450 Hz effectively excludes signals with the potential to be "folded back" and interfere with the signals of interest.

Analog-to-digital (A/D) conversion of the signal is performed by the NI BNC USB-6216 DAQ module. For an analog signal input range of -5 V to 5 V, the voltage range spanned by each code of the 16-bit ADC, or its resolution, is about 152.5 µV; due to the system's method of calibration, the nominal value is given as 160 µV [112]. As the digital codes are spread evenly across the analog range, this means quantization error is very minimal: up to 80 µV for each sample. The resulting signal-to-noise ratio due to quantization error specifically can be calculated using equation (3-1).

$$SNR = 20 \log\left(\frac{10}{0.00008}\right) = 101.94 \text{ dB} \quad (3\text{-}1)$$

The DAQ module is also equipped with an anti-aliasing filter, implementing a low-pass filter with a cut-off frequency of 750 Hz (though this is largely unneeded due to the attenuating already performed by the Delsys Bagnoli system above 450 Hz) [112]. Finally, the maximum rate at which samples from multiple channels can be acquired by the system is 10^6 samples per second, corresponding to a sample acquisition time of 0.001 nS; the error introduced by this delay is therefore extremely minimal [112] compared to software-based delays involved.

The Delsys Bagnoli electrodes were affixed to the upper and lower right arm of each participant; one to the biceps, one to the triceps, two to the forearm flexors, and two to the forearm extensors. The ground electrode was affixed to a bony point on the shoulder, the acromion, chosen to minimize chances of dislodging or shifting the ground electrode during experimental set-up or participant motion.

The movements selected for implementation for this research were as follows: hand close, hand open, supination (palm up wrist rotation), pronation (palm down wrist rotation), elbow flexion, and elbow extension. This selection of movements was based on the most common degrees of freedom available in current commercial prosthetic devices for patients with transhumeral amputations [14]. The output hand open/hand close movements were mapped from wrist extension and wrist flexion input movements by the user, as these movements were similar but gave substantially clearer and more distinguishable signals. Wrist flexion/extension was not implemented as an output movement category, as although it has been implemented experimentally in several studies, it is not currently available in commercial devices, and therefore wrist supination/pronation was chosen [113].

A system flow diagram connecting the aforementioned hardware components (Bento Arm; brachI/Oplexus, BioPatRec and TAC software; and EMG acquisition hardware) is illustrated in Figure 3-5 below. In order to minimize potential signal noise due to inadequate grounding, power to all systems was supplied from a single surge-protected and grounded outlet device.

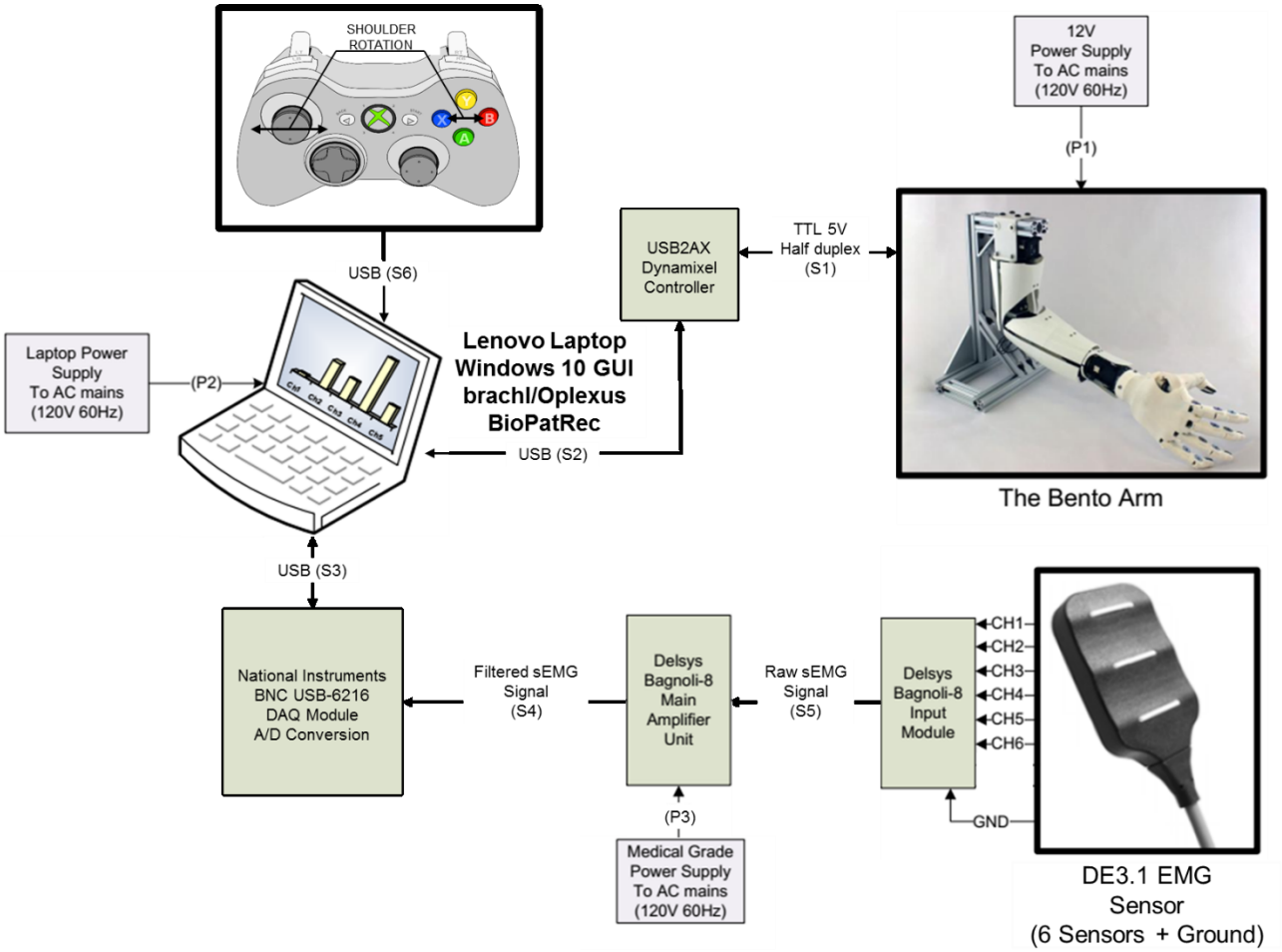

Figure 3-5: Hardware system flow diagram. Modified with permission from Dawson et al.

3.6 Desktop Evaluation Test

Use of desktop-mounted prosthetic devices to evaluate myoelectric control has primarily been limited to the modified Box and Blocks test utilized by Dawson et al. [69], based on the existing clinically validated Box and Blocks test [114]. However, the performance of this task with the desktop arm requires wrist flexion and extension, which was not a movement implemented in the pattern recognition controller applied for this study. Since the number of myoelectrically-controlled DoFs was being limited to three for feasibility and sufficient reliability of the PR-controller, supination/pronation was implemented instead due to the greater availability of wrist-rotators in commercial and research devices [14][113]. Another option was the clothespin relocation task, which is a simple functional task that does require wrist rotation; for this task, the participant must grasp and relocate three standardized Rolyan graded exercise pinch-pins from a horizontal bar to a vertical one, then back again [84]. A modified configuration of the clothespin relocation was developed for desktop evaluation using the Bento Arm, in such a way that only three degrees of myoelectric control were required: grip open/close,

wrist rotation, and elbow flexion/extension (humeral rotation, where necessary, was implemented through joystick control or automated from button pushes). However, the force produced by the current Bento Arm gripper was insufficient to pinch the clothespins open enough to remove them cleanly from the horizontal bar while preventing slippage, rendering the task extremely challenging. Incorporation of this task into the evaluation metrics was therefore considered unviable until a more powerful gripper configuration for the Bento Arm is developed in future.

Given the lack of appropriate existing desktop functional evaluations, a custom task was developed for this purpose: the Cup Deposition test. Using the desktop-mounted Bento Arm, this task requires the user to grasp a cup from a starting position and perform various manipulations before releasing it into a depository. It was designed to be easily configurable to test any of the different degrees of freedom of the Bento Arm that could be operated by myoelectric control, including gripper open/close, wrist flexion/extension, forearm supination/pronation and elbow flexion/extension. The task can be easily broken down into defined phases and minimum required movements, yet still relates to use of a prosthetic device in activities of daily living (grasping and moving objects). The full step-by-step protocol for performing the Cup Deposition test is described in section 4.2.5.

Data logging during the task was set to be triggered automatically by the participant pressing a button on an Xbox controller with their free hand in order to initiate the first automated motion and start the trial, and to finish when the gripper opened to a degree sufficient to release the cup while above the end position. Logged data included time for each trial, angular position of all the Bento Arm joints, and electrical load on the gripper servo motors, which could be correlated to the grip force applied by the gripper (see Appendix B) on the objects being manipulated to indicate excessively tight or loose grasp action by the participant. The position logs allowed individual trials to be compared against a theoretical perfect completion of the task, indicating delays, erroneous motions, or overshoots and undershoots that could be correlated with the video recordings as needed.

3.7 Desktop Training Protocol

A protocol for training myoelectric control using the desktop-mounted Bento Arm was developed based on previous training protocols developed by Dawson et al. for the Myoelectric Training Tool (MTT) [9], input from an experienced occupational therapist, and recommendations from protocols developed at the Research Institute of Chicago by Simon et al. [8] and similar work by Powell [100] and Stubblefield [101]. This protocol was designed to improve the user's control of each degree of freedom using simple object manipulation across a varied desktop training environment, then adding a new degree of freedom to the control scheme and corresponding practice tasks once each previous degree of freedom has been mastered. Practice tasks and training protocol are described in full in section 4.2.4.

4.0 Experimental Study

4.1 Introduction

Myoelectric prostheses with multiple degrees of freedom are difficult to control due to a limited number of input signals [1][2]. This limitation can make them slower and less intuitive to use, hence discouraging widespread adoption and limiting their ability to improve quality of life for persons with amputations [3][4]. A variety of myoelectric control strategies attempting to address these issues have seen intensive research and development over the past few decades. In particular, pattern recognition (PR) allows multiple DoFs to be controlled even with a limited number of muscle sites and myoelectric input signals [32]. Despite an abundance of development work [5], unlike conventional myoelectric control [14], pattern recognition has only recently been transitioned to commercially viable products [52][53]. A change in control strategy may result in increased training and configuration requirements for users [5][25] and potentially higher cognitive demand of the user to control additional DoFs [14].

Despite its significant impact on performance and its importance to rehabilitation, the effect of user training with differing myoelectric strategies has not been thoroughly investigated and assessed [6][7] with functional task evaluations, partially due to the intense requirements for training and fitting a final socket-mounted prosthesis and the scarcity of commercially available PR-control based prosthetic devices [5]. Training and evaluation in virtual space is common, but very limited in simulation of prosthesis operation or object interaction [6][96]. Desktop-mounted robotic arms offer a number of potential benefits as an intermediate research and training platform for prosthetic control [8][9]; these include no socket fitting or mounting requirements, thereby reducing set-up requirements and confounding factors in testing [5], and the ability to be used by both able-bodied and individuals with amputation. However, the correlation of measured performance between socket-mounted wearable prostheses and other platforms (desktop or virtual) have only minimally been studied [78], rendering it difficult to incorporate these intermediate platforms into meaningful myoelectric control strategy design, selection, or training protocols.

The experimental study described here aims to address the gap in lack of validated performance measures for desktop training systems as a first required step in being able to compare myoelectric control strategies across different evaluation platforms. The overall goal was to design a training and evaluation protocol using a desktop robotic arm to evaluate and compare myoelectric prosthetic control strategies, and to validate this in inexperienced (minimal to no myoelectric training experience) able-bodied participants.

For validation, the quality of a test or measurement can be described by a number of psychometric properties; these include reliability and validity, responsiveness, floor/ceiling effects, and other properties [92]. **Reliability** refers in general to "the consistency of a test or measurement" [115], but approaches to quantifying reliability differ depending on what varying factor the test's consistency is being measured against. Different forms of reliability include internal consistency, test-retest reliability, inter-rater reliability and intra-rater reliability [92]. Weir identifies **test-retest reliability** as the most common and useful form in biomedical literature [115]. In this context, Resnik et al. define this attribute, often referred to as repeatability, as measuring the stability of a test under the same conditions at different points in time [92]. This makes it an important first property to verify for a novel test such as the desktop evaluation designed for use in this study; and, as it does not require comparison to another previously validated test, it is also one of the most straightforward initial psychometric properties to examine. In addition to establishing test-retest reliability, another psychometric property that can be assessed is **concurrent validity** [92], which indicates how well results from this test correlate to results on another, previously established test. Lastly, assessing training effect, whether the desktop training protocol was effective in improving participant performance, can be determined by examining the pre-training and post-training performance scores and determining statistically whether the differences indicate improvement.

4.1.1 Experimental Questions

This study had two main aims: to implement a myoelectric control training protocol using a desktop-mounted robotic arm, and to develop a novel performance evaluation designed for the desktop robotic arm setup, the Cup Deposition test. The effect of the training protocol on performance was assessed with a previously established virtual test of PR-based control in a simulated environment, the Target Achievement Control (TAC) test [81]. The TAC test was applied pre-training and post-training, and compared to the post-training performance on the Cup Deposition test.

The specific questions addressed were:

1) Whether the desktop training protocol results in a significant difference in performance on the pre-training and post-training TAC tests.
2) Whether the Cup Deposition test demonstrates test-retest reliability between two evaluation blocks.
3) Whether the Cup Deposition test demonstrates concurrent validity through correlation of participant performance on the post-training TAC test.

4.2 Experimental Protocol

A total of 11 able-bodied participants (3 male and 8 female, mean age and SD 27.0 ± 7.0 years) were recruited for a 3-hour training and evaluation session. Participants were recruited by informal communication, and from respondents to flyers (see Appendix D) that were posted around the University of Alberta North Campus. Ten participants were right-handed, 1 was left-handed; all participants were inexperienced with myoelectric control (minimal to no myoelectric training). All procedures and protocols were approved by the University of Alberta Research Ethics Board (REB 2) and written informed consent was obtained from all participants. The hardware for the experiment (described in Chapter 3, briefly summarized here) consisted of an 8-electrode Bagnoli system, NI BNC USB-6216 DAQ block, cart-mounted Bento Arm, laptop and monitor, Xbox controller, lower arm brace mounted to chair arm-rest, training and familiarization workspace and objects, and Cup Deposition test workspace and objects. The experimental session protocol is detailed in Table 4-1, which includes a detailed summary of the structure of each session and the time allocated to each of the steps. Short breaks (1-5 minutes) were enacted when participants indicated they were fatigued, in addition to enforced 5-minute breaks after each experiment phase.

Table 4-1: Experimental Session Structure and Steps

Phase	Steps	Time allocated (minutes)
Initialization and Calibration	Electrode placement	10
	Initial Calibration	15
	Calibration Corrections	15
Pre-training Target Achievement Control Test	1-DoF TAC Test	5
	2-DoF TAC Test	10
	3-DoF TAC Test	10
Training	1-DoF Familiarization and Training Tasks	10
	2-DoF Familiarization and Training Tasks	20
	3-DoF Familiarization and Training Tasks	25
Desktop Evaluation Block A	1-DoF Cup Deposition	5
	2-DoF Cup Deposition	10
	3-DoF Cup Deposition	10
Desktop Evaluation Block B	1-DoF Cup Deposition	5
	2-DoF Cup Deposition	10
	3-DoF Cup Deposition	10
Post-training Target Achievement Control Test	1-DoF TAC Test	5
	2-DoF TAC Test	10
	3-DoF TAC Test	10
Usability Survey		5

4.2.1 Experimental Set-up

Each participant was seated in a chair positioned in front of the desktop test environment. Four electrodes were placed on their right forearm and two on their right upper arm, and a ground pad on their right shoulder acromion (bony prominence). The participant was asked to make simple motions with the arm (wrist flexion/extension, forearm supination/pronation, elbow flexion/extension) in order to identify prominent musculature for optimum electrode placement. After the electrodes were placed and wrapped in bands of gel-based socket liner material (constructed from WillowWood Alpha Classic® Liner) for compression and stability, it was confirmed in BioPatRec that all electrodes were reading a detectable level of EMG signals during muscle activation. The participant's right arm was then placed in a wrist brace and restrained to the armrest of the seat using Velcro straps to enforce isometric muscle contractions [116], as illustrated in Figure 4-1, with an elbow stopper placed behind their elbow to maintain consistent position.

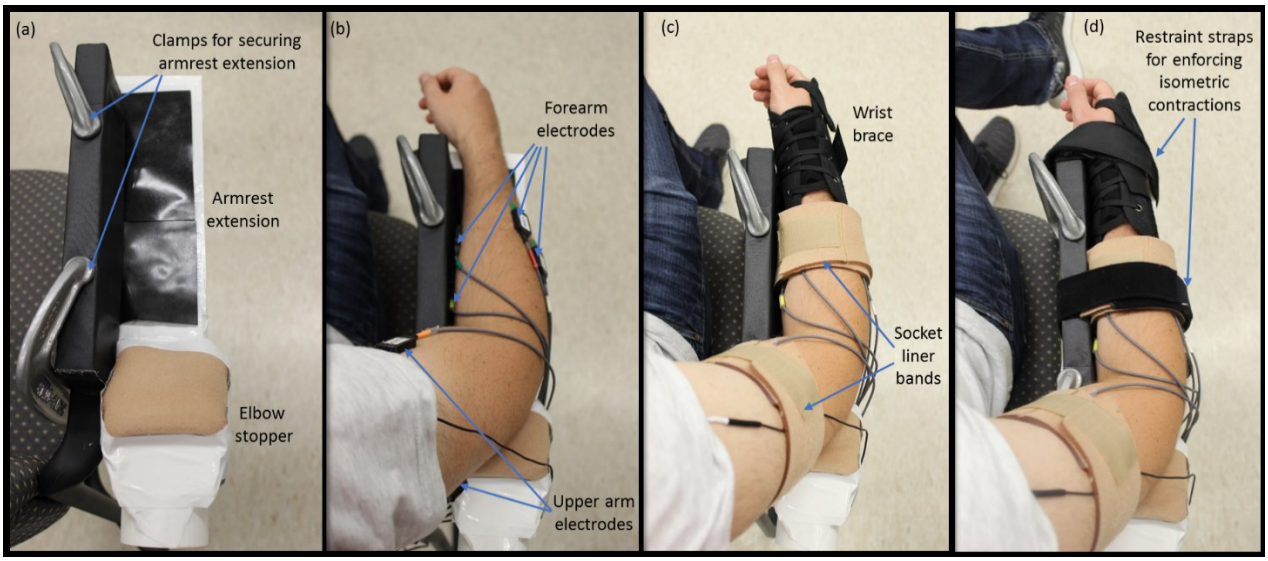

Figure 4-1: Experimental set-up of participant's arm on chair armrest, showing a) empty chair with armrest extension clamped to chair armrest, b) participant's right forearm with electrodes on forearm and upper arm, c) participant's forearm with wrist brace and socket liner bands over electrodes, and d) restraints on participant's forearm enforcing isometric contractions.

4.2.2 Initialization and Calibration

To calibrate the pattern recognition controller, the participant performed three repetitions of each of the six designated input movements (constrained so as to result in isometric contraction), alternating 3 seconds of contraction with 3 seconds of rest [38]. Textual cues for the movement inputs in simple terms (for example, "Bend Wrist Inwards") were delivered visually on a monitor, accompanied with an image of the requested movement. A preliminary pattern recognition data analysis for verification was

performed on the calibration recordings through BioPatRec to identify inconsistent or conflicting calibration patterns. These were re-recorded until seven non-conflicting recording patterns (including rest) were produced. Where distinguishability proved challenging between two movements, the participant was asked to vary aspects of one of the movements (ex: finger positioning, muscles emphasized during the movement) until a distinguishable pattern that could be performed consistently was achieved.

Calibration signal recordings were treated with a notch filter at 60 Hz to remove power line noise and a band-pass filter with cut-off frequencies of 20 Hz and 495 Hz to remove leftover motion artifacts, then divided into windows of 200 ms and increments of 50 ms. A Linear Discriminant Analysis (LDA) controller was chosen for its reliability, simplicity and relatively comparable performance to other classifiers [5][37]. The controller was produced from the top four time-domain features of the calibration recording: amplitude mean absolute value, waveform length, zero crossings and slope sign changes [32][44] The confusion matrix of offline classification accuracies was verified to be within the minimum error range (±2.04%) of 100% before continuing; any movement classes with a classification accuracy under 97.96% were re-recorded. The Virtual Reality Environment in BioPatRec was used to verify that the desired movements were achievable.

4.2.3 Target Achievement Control Test

Following set-up and prior to desktop training, participants completed a pre-training TAC test to assess their baseline level of myoelectric control for three levels: one DoF per trial, two DoFs per trial, and three DoFs per trial; a full list of the resulting movement combinations involved in each level of the test is shown in Table A-1 in Appendix A. For each test, two repetitions of each movement or movement combination were assessed, in a randomized order. Based on the recommended TAC test default settings and previous studies [44][45], allowance was set at ±5 degrees, required hold time at 2 seconds, and time-out limit per trial at 15 seconds per degree of freedom (15 for 1-DoF, 30 for 2-DoF, and 45 for 3-DoF). For every trial in each of the TAC tests, recorded data included completion rate (whether the target position was reached before timeout), completion time (time to reach target position, not including hold time), and path efficiency (minimum angular displacement required to reach target divided by actual angular displacements).

4.2.4 Desktop Training

Following the baseline TAC test, 60 minutes were allocated towards training the participants in PR-based control using the desktop-mounted robotic arm, according to the protocol developed in section

3.7. The protocol was designed to improve the user's control of each DoF using simple object manipulation tasks across a training environment with three distinct areas at different elevations, illustrated in Figure 4-2a; additionally, a full view of a participant seated in front of the training area manipulating an object can be seen in Figure A-1 in Appendix A.

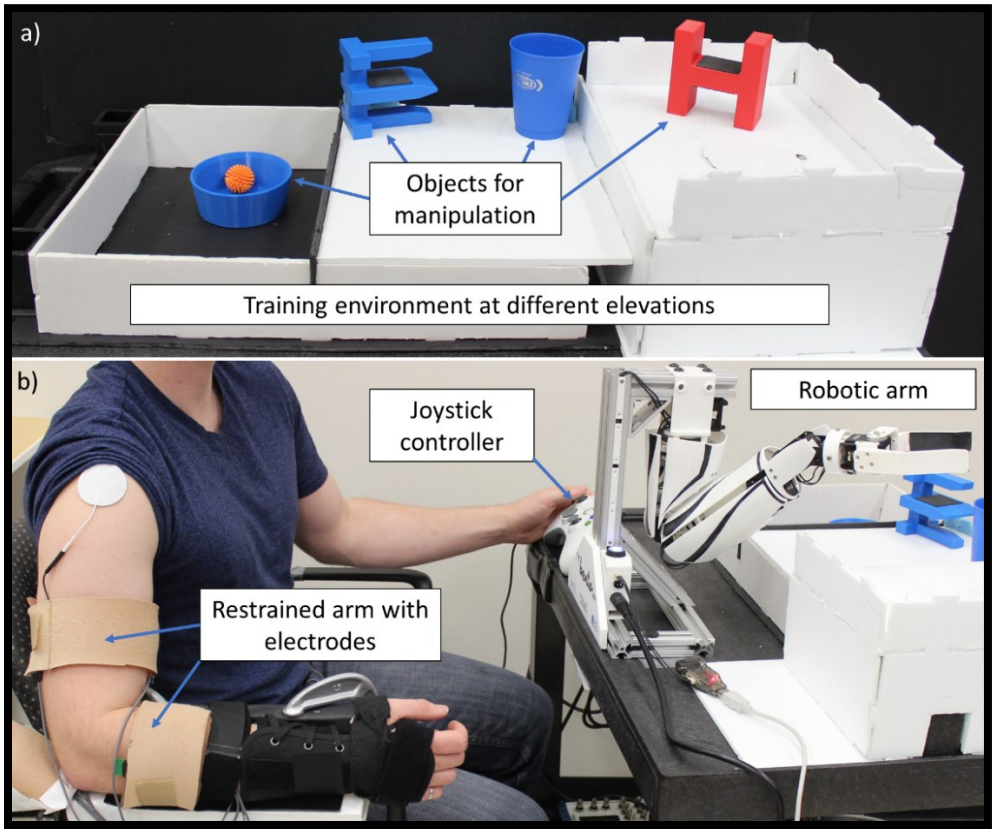

Figure 4-2: Training environment for desktop-mounted robotic arm, showing a) three distinct surface areas at different elevation levels and various objects for manipulation, and b) participant with electrodes attached to restrained right arm, controller for left hand, and desktop-mounted Bento Arm.

Training was carried out starting with only a single degree of freedom enabled (gripper open/close), then adding forearm supination/pronation (wrist rotation) control, and then enabling elbow flexion/extension. The horizontal position of the end-effector on the training environment was controlled by the participant using their left hand to manipulate a joystick that activated humeral rotation of the robotic arm. For each DoF added, the participant was first asked to practice actuating the new DoF to different angular positions at varying speeds, as well as to repeat practice movements with previously learned DoFs to ensure they could be activated without confusion with new DoFs or unintentional movement. For each DoF, the participant then performed a series of simple practice tasks manipulating objects in the desktop training area, described in Table 4-2. Individual pictures of the described objects for manipulation can be seen in Figure A-2 in Appendix A. The participant was

required to complete each task a minimum of 5 times with a minimum success rate of 70% to move on to the next degree of freedom.

Table 4-2: Training Protocol Practice Task Descriptions

DoF	Joint	Movements	Tasks	Description
1	Gripper	Open/ close	H-block drop	Grasp red H-block, position over pit, release
			Cup drop	Grasp cup, position over bowl in pit, release
2	Forearm	Supination/ pronation	H-block rotate & drop	Grasp red H-block, position over pit, pronate 90°, release
			Cup pour	Grasp cup with ball inside, position over bowl in pit, pronate 90° to pour ball into bowl, supinate 90°, return cup to starting position and release
			W-block rotate & drop	Grasp blue W-block about center prong, position over pit, pronate 90°, release
3	Elbow	Flexion/ extension	H-block raise & rotate	Grasp red H-block, raise to clear upper level, position over upper level, pronate 90°, release
			Cup raise and pour	Grasp cup with ball inside, raise to upper higher level, position over bowl on upper level, pronate 90° to pour ball into bowl, supinate 90°, return cup to starting position and release
			M-block raise & rotate	Grasp purple M-block about center prong, raise to clear upper level, position over upper level, pronate 90°, lower and release

4.2.5 Desktop Evaluation

After training with the desktop-mounted prosthetic device, the participant completed two blocks of desktop control evaluations, each consisting of three levels of test: 1-DoF (gripper only), 2-DoF (gripper and forearm rotation), and 3-DoF (gripper, forearm rotation and elbow flexion/extension). For each test, the task of moving the cup from the starting position to the repository was described and demonstrated step by step using joystick control of the Bento Arm, then allowing the participant one practice run at a slow, comfortable pace before tests were logged, to ensure they fully understood the directions. It was explained to the participant that their goal is to complete the task successfully and efficiently, noting that both errors and time taken will be tracked, and that multiple repetitions of each task will be performed.

For the 1-DoF Cup Deposition test, the test bench was set-up according to Figure 4-3 and the corresponding brachI/Oplexus profile joint limits loaded. For this test, the participant initialized a trial by pressing the X-button on the Xbox controller, which automatically moved the arm from the depository to the starting position, in which the gripper was open and its fixed digit was touching the cup on the stand. Using myoelectric control, the participant closed the gripper on the cup. Once the cup was

grasped, they pressed the B-button to automatically move the arm to the finishing position above depository 1. The participant then used the myoelectric control to open the gripper which released the cup to drop it into depository hole 1. This task was performed 15 times, with the test administrator qualitatively noting failed trials (trials in which the cup is prematurely released and therefore not successfully deposited in the depository) as well minor errors that did not result in task failure, categorized according to phase (pick-up phase, transport phase, release phase) and type (overshoot or undershoot, erroneous motions, or extensive delay).

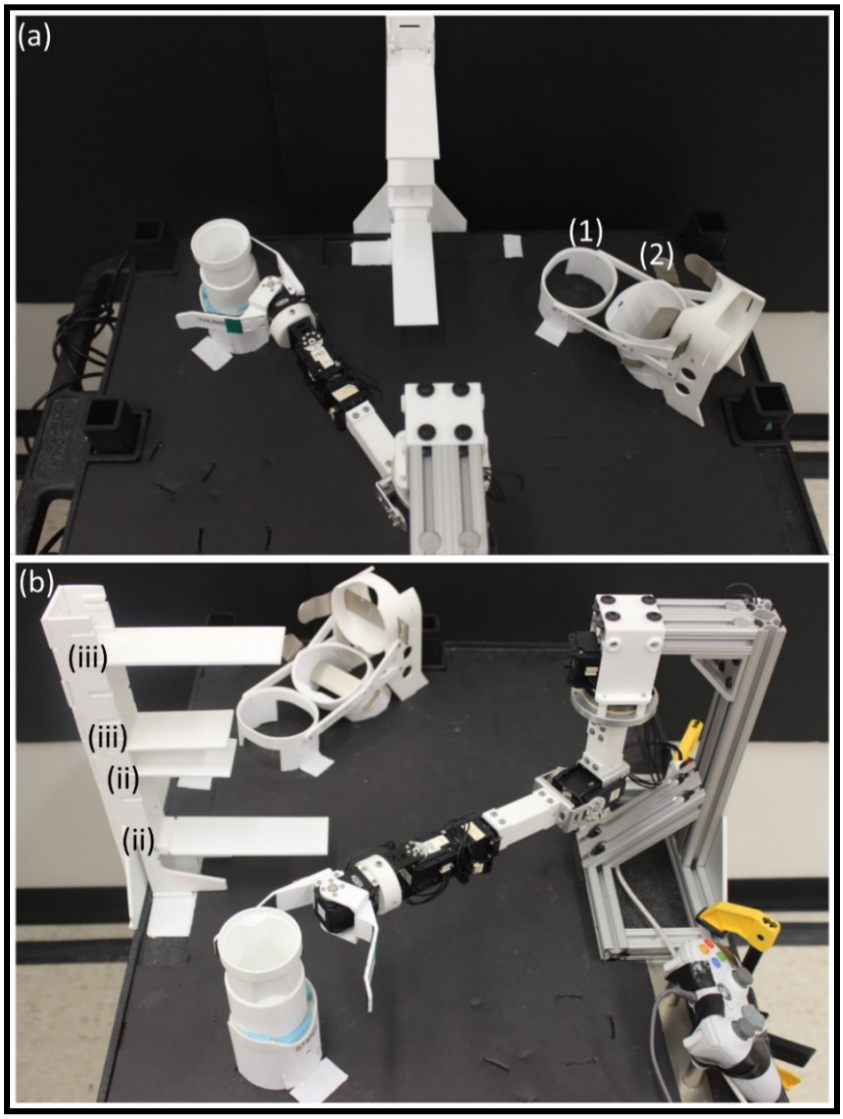

Figure 4-3: The Cup Deposition test set-up, from a) front view, and b) side view. For the 1-DoF test, depository (1) is used and no planks are mounted; for the 2-DoF test, depository (2) is used and planks are mounted at the (ii) positions (as shown in b); for the 3-DoF test, depository (2) is used and planks are mounted at the (iii) positions. Individual plank tower configurations can be seen in Figure A-3 in Appendix A.

After it was confirmed that 15 trials were logged successfully, the participant proceeded to the 2-DoF Cup Deposition test. The test bench was set-up according to Figure 4-3 and the corresponding brachI/Oplexus profile joint limits loaded. For this test, after gripping the cup, the participant had to rotate the cup by pronating the wrist to approximately 90 degrees in order to pass between the two planks in the central tower when they pressed the B-button. Once the cup had been repositioned above the repository, they then had to rotate the cup by supinating approximately 45 degrees and open the gripper to deposit the cup in depository 2. Again, 15 repetitions were performed with failures and errors being qualitatively noted.

The participant then proceeded to the 3-DoF Cup Deposition test, where the test bench was set-up according to Figure 4-3. After gripping the cup, the participant had to both rotate the cup to 90 degrees (by pronating) and raise the cup using elbow flexion to its maximum height, in any order, to be able to pass between the two planks in the central tower when they pressed the B-button. Once the cup had been repositioned above the repository, they then had to rotate the cup approximately 45 degrees (by supinating) and lower the cup to its minimum height using elbow extension, then open the gripper to deposit the cup in depository 2. Again, 15 repetitions were performed with failures and errors being qualitatively noted. After confirming 15 trials were logged successfully, Block A (which consisted of the 1-DoF, 2-DoF, and 3-DoF Cup Deposition tests) was concluded. A five-minute break was enforced to allow the participant to relax before performing evaluation Block B. This block proceeded identically as Block A through the three test levels; once completed, another five-minute break was enforced before switching control back to the virtual arm and completing the post-training TAC test, which was run identically as the pre-training TAC test described in section 4.2.3.

4.2.6 Usability Survey

After the completion of the second TAC test, the participant's right arm was released from the isometric contraction constraint, and the electrodes were removed from their skin; they then completed the usability survey shown in Appendix C, based on a similar survey developed by Brenneis et al. [117]. Here, they rated the intuitiveness of the myoelectric control strategy used, the effectiveness on each of the evaluation tasks, and the reliability in terms of unintended motions, using a Visual Analogue Scale (VAS). The participant also ranked the movements of the Bento Arm in terms of which was easiest to control, specifying what aspect of the most difficult movement made it challenging, and noted which desktop training activity, if any, they felt was the most beneficial to improving their control over the Bento Arm.

4.3 Data Collected

Data was recorded and analyzed from all participants. Due to technical difficulties and time limitations, full pre-training TAC test data was not obtained for one participant, and full block B Cup Deposition test data was not obtained for another participant; therefore, from the 11 participants whose data was analyzed, 10 data sets were acquired for the Cup Deposition test test-retest validity analysis, 10 data sets were acquired for the TAC test pre-training and post-training difference analysis, and 9 data sets were acquired for the concurrent validity analysis assessing correlation between participant performance scores on both tests.

4.3.1 Cup Deposition

For each trial in each of the Cup Deposition tests, the brachI/Oplexus automatic logging function recorded the angular position of each Bento Arm joint and the voltage load for the Bento Arm gripper, along with the corresponding timestamp for every brachI/Oplexus cycle (approximately every 5 to 10 milliseconds), from the initialization of the trial to the release of the cup above the goal depository or, in the case of a failed trial, until manual cancellation. These data logs could be used to reconstruct each trial for validation and analysis. An example of a reconstructed trial can be seen in Figure 4-4a, which illustrates the joint angles over time of the robotic arm under control of a participant performing the 3-DoF Cup Deposition test. The required movements for the task can be categorized as the transitions between 8 intermediate positions of the robotic arm, labeled on the plot and illustrated with pictures underneath (the transition from position 0 to position 1 is the automated movement to the trial starting position). The dotted lines in Figure 4-4b demonstrate a theoretically perfect completion of the task as performed by the pre-programmed automatic test demonstration.

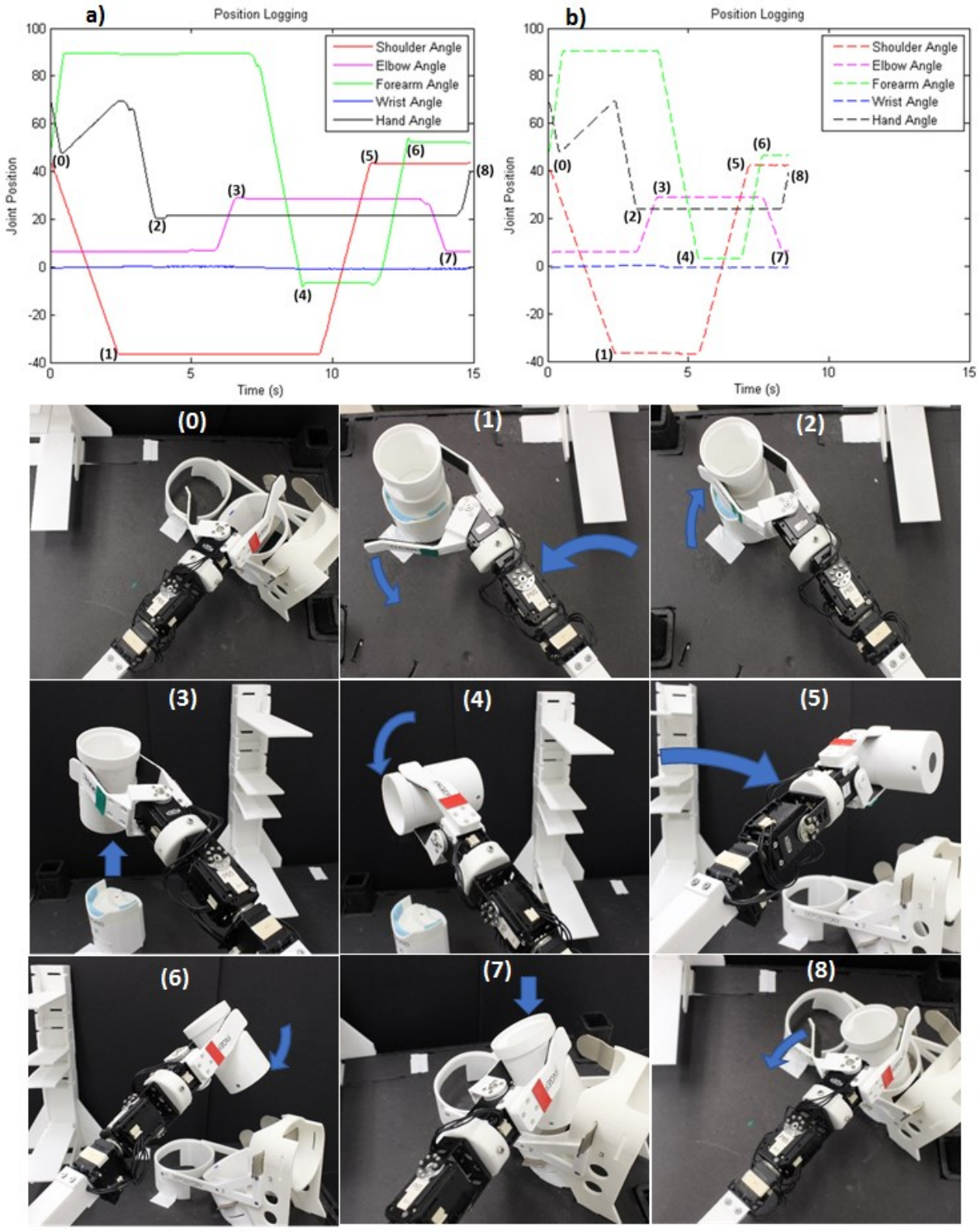

Figure 4-4: Plotted angular position logs of Bento Arm joints during 3-DoF Cup Deposition test, as performed by (a) a participant, and (b) automated pre-programmed movements. Positions after each movement in the trial, denoted 0-8 in the log plots, are illustrated in respective photographs of the Bento Arm underneath.

From this data, each trial had a calculated completion time, completion status, and path efficiency. Logged completion time was calculated from the trial initialization button press to the opening of the gripper over the final position, or manual trial cancellation due to the cup being dropped (in which case the time was discarded during analysis). Completion status for a single trial was recorded as either 1 if successful, or 0 if the completion time exceeded the timeout value for that DoF test. The timeout value was set to be 3 times the minimum completion time performed by the automatic demonstration, as in Table 4-3; this time limit on successful task completion is similar to the timeout limit incorporated into the Target Achievement Control test [81], and effectively helps to limit completion time outliers that could result from trials deviating heavily from the task goal. Averaging across the 15 trials, the completion rate for the full test at that DoF level was therefore the percentage of successfully completed depositions (trials with a completion status of 1) across the full set of 15 trials.

Table 4-3: Cup Deposition Test Minimum and Maximum Completion Time Values

Cup Deposition Test DoF	**Minimum Completion Time (Automated Completion)**	**Maximum Completion Time (Timeout Value)**
1	4.61 seconds	13.83 seconds
2	7.14 seconds	21.43 seconds
3	8.60 seconds	25.80 seconds

Path efficiency was calculated as the minimum angular displacement required to reach the target, as performed by an average automated completion of the test, divided by actual angular displacements made when controlled by the participant. Specifically, an automated completion of the test was run 5 times at each level to determine the minimum angular displacement from the average of those automated runs. Participant controlled angular displacement was calculated as the difference in angle values of user-controlled joints between successive position logs, summated over the duration of the entire trial. Path efficiency was effectively capped at 1.00 for each DoF, to avoid participant shortcuts in one DoF (such as releasing the cup before rotating fully to 45°, but not enough to fail the test) from concealing inefficiencies such as overshoot or unnecessary movement made in other DoFs.

Qualitative tester observation was required to note tests failed due to premature cup release before the depository; these were then denoted as unsuccessful completions as well (completion status of 0) for the final calculation of the overall test completion rate. To complement path inefficiency information, observed minor errors that did not result in task failure were also recorded, categorized according to phase (pick-up phase, transport phase, release phase) and type (overshoot or undershoot,

erroneous motions, or extensive delay). The tasks in the training protocol preceding the Cup Deposition test were not logged, but were qualitatively observed for failure/success to guide the training, and any participant comments or other qualitative information that could guide the desktop training process were recorded.

4.3.2 Target Achievement Control Test

For each trial in the TAC tests, the angular position of the virtual limb in each of the three DoFs was recorded at every timestep (0.05 seconds), until the trial was either completed by successfully maintaining the position of the virtual limb within allowance of the target position for 2 seconds, or failed by exceeding the time limit. The three metrics drawn from this data for each trial were trial completion, completion time, and path efficiency [81]. Trial completion simply defined whether the target position was reached before timeout (15 seconds for 1-DoF, 30 seconds for 2-DoF, and 45 seconds for 3-DoF [44]), which could in turn be used to calculate the completion rate percentage for the overall test. Completion time measured the time required to move the virtual arm to the target position, not including the required hold time. Path efficiency was calculated from the minimum angular displacement required to reach the target, divided by the sum of the actual angular displacements made by the participant, including both erroneous motions through incorrect DoF and overshoot in the correct DoF [81]. Notably, for TAC test trials requiring combination movements across two or more DoFs, the most direct path to the target position requires moving through both DoFs at the same time; since simultaneous movements were not included in this experiment, the maximum possible path efficiencies for 2-DoF and 3-DoF trials in this study were $\sqrt{1/2}$ and $\sqrt{1/3}$ respectively, or 70.7% and 57.7%.

4.3.3 Usability Survey

Usability survey data consisted of subjective ratings by each participant on how they perceived three different attributes of the myoelectric control system: intuitiveness (how easy it was to learn to use the controller), reliability (how often the controller acted in an unwanted or unexpected way) and effectiveness (how well the controller was able to perform each of the different tasks: 1-DoF Cup Deposition, 2-DoF Cup Deposition, 3-DoF Cup Deposition and TAC test). Responses were recorded on a Visual Analogue Scale (VAS), where participants marked their rating on a line of a defined length, with extreme cases denoting each of the end points (for example, not difficult at all or extremely difficult); this distance along the line was then measured and converted to a continuous percentage score. In addition, usability survey data included the participant's ranking of the Bento Arm movements by ease

of use (from 1 to 6), qualitative description of the difficult aspects of most challenging movement, and qualitative description of their preferred desktop training activity.

4.4 Data Analysis

4.4.1 Preliminary Data Analysis and Preparation

Evaluation data was recorded in an excel spreadsheet, with one worksheet per participant. Each worksheet contained all relevant information for the participant's test performance, including:

1. For the Cup Deposition test and desktop training:
    - Cup Deposition test results from log files (completion rate, completion time, path efficiency)
    - Qualitatively observed Cup Deposition test errors
    - Training task completion rate
2. For the TAC test:
    - TAC test results from MATLAB (completion rate, completion time, path efficiency)
3. For the usability survey:
    - Summary of usability survey results (VAS responses, movement ease-of-use ranking, qualitative comments)
4. Other qualitative information:
    - Non-identifying participant data
    - General participant comments or experimenter notes pertaining to the session, and the time at which they were noted

4.4.2 Preliminary Data Visualization

Raw TAC test results and Cup Deposition results logged in MATLAB were imported manually into each sheet. Each sheet also included preliminary test visualization tools such as Cup Deposition completion time curves (with failed tests removed) and box-and-whisker plots. A sample series of completion time curves can be seen in Figure 4-5 for evaluation block A and B.

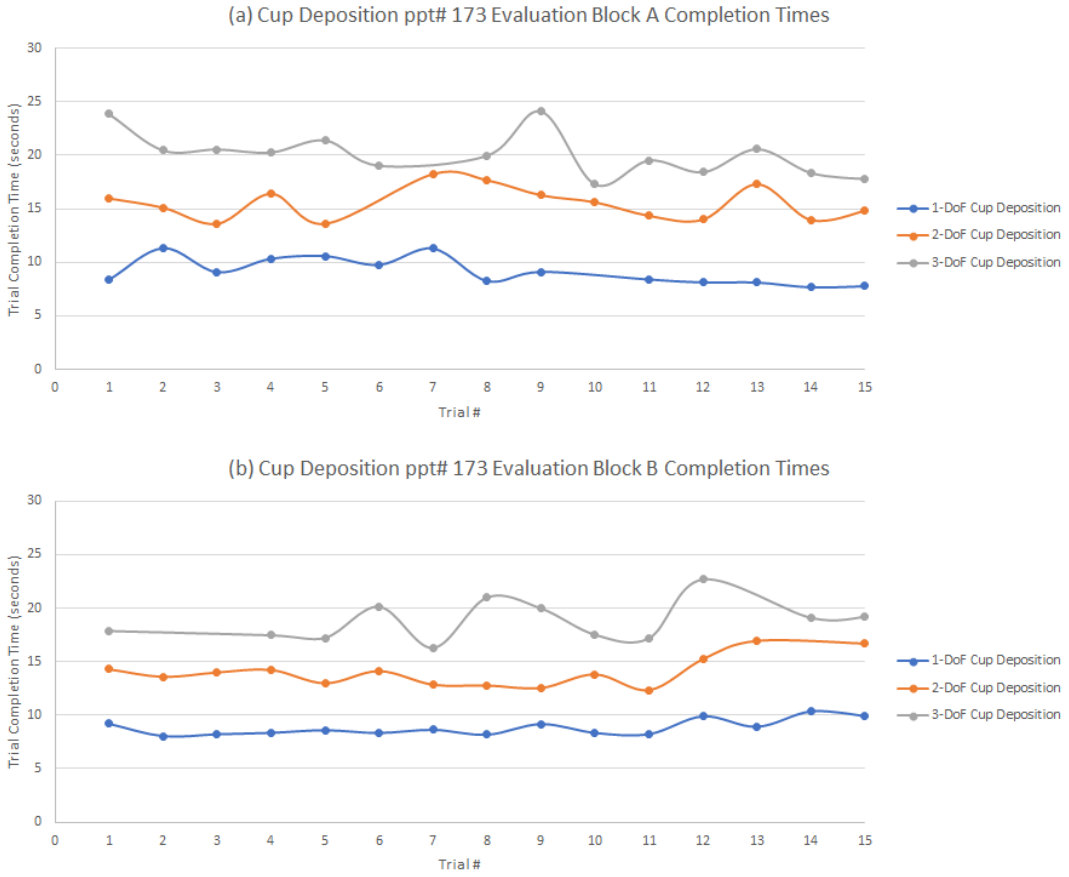

Figure 4-5: Sample participant completion time curves with failed trials removed for 1-DoF, 2-DoF and 3-DoF Cup Deposition test in (a) evaluation block A, and (b) evaluation block B

4.4.3 Cup Deposition Data Subdivision

Cup Deposition test completion time curves for each participant were divided into three stages; an initial learning stage characterized by improvement and some inconsistency as the participant adjusts to the test, a plateau stage characterized by relatively consistent performance [115][118], and (in some cases) a tail stage characterized by less consistency and greater fatigue effects. The plateau stage was identified by first determining every possible set of trial boundaries for a plateau of minimum length 5 trials, maximum length 10 trials, starting at any trial in the test. Then for each level of the test (1-DoF, 2-DoF and 3-DoF in block A and block B), the most consistent plateau stage among the participants was

identified by running a MATLAB script to fit linear regression curves to all possible plateau stages of every participant's test completion times, then optimizing for the plateau boundaries that minimize the average plateau slope magnitude. Learning stages and tail stages were assumed to comprise the remaining trials on either side of the plateau stages; the plateau regions were considered the more important stages of interest, since they represent the most stable and consistent performance results least affected by either learning effects or fatigue, as indicated by their regression curve slope values approaching zero.

4.4.4 Assessment of Normality

IBM SPSS Statistics software (IBM Corp, Released 2017, IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp) was used for all statistical analyses, except where otherwise indicated. In order to verify whether parametric statistical analyses could be applied, data extracted from both the Cup Deposition and the TAC tests were checked for a normal distribution of data using the Kolmogorov Smirnov (KS) test and corresponding p-values.

4.4.5 Cup Deposition Test-Retest Reliability

Test-rest reliability can be assessed using the Intraclass Correlation Coefficients (ICC) for continuous data sets [92][115], following guidelines laid out by Weir [115]; similar analysis has been performed by Shehata et al. on various myoelectric prosthesis control performance scores [119]. Accordingly, the test-retest reliability of the Cup Deposition test was assessed using a two-way random ICC model. A repeated measures ANOVA was used to generate the ICC values between the set of all participants' block A average scores and the set of all participants' Block B average score. The ANOVA F-statistic values and p-values were also examined to determine whether significant differences between block A and block B scores existed.

Standard Error of the Measurement (SEM) values were calculated using equation (4-1) recommended by Weir et al. [115].

$$SEM = SD\sqrt{1 - ICC} \tag{4-1}$$

For data that did not meet normality requirements, a non-parametric equivalent was applied: Kendall's W Statistic, which yields a Coefficient of Concordance (CC).

4.4.6 Pre-Training and Post-Training TAC Test Differences

Determining whether the desktop training protocol was effective in improving participant myoelectric control requires examining the pre-training and post-training TAC test performance scores and determining whether differences indicate a systemic improvement. This type of analysis can be performed using the repeated measures ANOVA, which indicates to what extent the difference in two paired sets of scores is influenced by the intervention as compared to the random error (noise) inherent in the data sets. Similar analysis was performed on pre-training and post-training myoelectric control performance scores by Hargrove et al. [94], including TAC test results. For data that did not meet normality requirements, a non-parametric equivalent for comparing two paired data sets, the Wilcoxon signed-rank test, was applied instead [120].

4.4.7 Cup Deposition to TAC Test Correlation

Finally, the Cup Deposition test and TAC test results were compared via correlation in order to assess whether the Cup Deposition test scores reflected performance similarly to the TAC test scores, thus indicating the concurrent validity of the novel desktop evaluation. Assessment of concurrent validity can be performed by plotting participant scores on the test in question against participant scores on a previously validated measure of similar construct, and determining the correlation of a regression curve fitted to these data points from its R^2 value [92]; the Pearson correlation coefficient can also be produced directly from a Bivariate Pearson analysis. This approach has previously been used to compare myoelectric control performance scores on different test platforms by Vujaklija et al. [76] and to compare Target Achievement Control test completion time scores and ACMC Scores by Hargrove et al. [107].

Cup Deposition completion time, completion rate and path efficiency participant scores, averaged between the two evaluation blocks for each participant, were correlated against TAC test completion time, completion rate and path efficiency participant scores respectively, using a Bivariate Pearson correlation to calculate the Pearson correlation coefficients. Excel was used to perform linear regression curve fittings between the three aforementioned Cup Deposition and TAC test scores for visual representations. For data that did not meet normality requirements, a non-parametric equivalent was selected: Spearman's rank correlation coefficient (Spearman's rho).

4.5 Results

The results obtained from applying the statistical analyses described in section 4.4 are presented here for each of the data sets analyzed.

4.5.1 Cup Deposition Data Subdivision

The boundaries of the approximate stages into which the Cup Deposition test data was subdivided, derived from the MATLAB plateau stage boundary optimization script, are shown in Table 4-4. The plateau regions were the more important stages of interest, since they represented the most stable and consistent performance results least affected by either learning effects or fatigue [118], as indicated by their minimized average regression curve slope magnitude.

Table 4-4: Optimized Boundaries of Completion Time Curve Stages for Each Level of Cup Deposition Test

Cup Deposition Test DoF		**Stage 1 (learning)**	**Stage 2 (plateau)**	**Stage 3 (tail)**
1-DoF:	Block A	Trials 1-5	Trials 5-14	Trial 15
	Block B	Trials 1-2	Trials 2-12	Trials 13-15
2-DoF:	Block A	Trials 1-4	Trials 4-14	Trial 15
	Block B	Trials 1-4	Trials 4-14	Trial 15
3-DoF:	Block A	Trials 1-5	Trials 5-15	N/A
	Block B	Trials 1-2	Trials 2-12	Trials 13-15

Notably, the training stages lasted longer and the plateau stages started later in the block A tests as compared to the block B tests; this can be understood as the participant requiring more trials to adjust to each level of the test when performing it for the very first time, but requiring fewer trials to plateau during the second block as they are already familiar with all of the tests. Post-plateau stages, indicating steeper regression slopes due to inconsistency in completion times, only appeared for the block B tests, where fatigue would have been a greater factor for the participants.

An example of a participant completion time curve divided according to the boundaries specified in Table 4-4 is depicted in Figure 4-6; a negative regression curve slope value represents a decrease in completion times, indicating a learning effect, whereas a slope close to zero indicates relatively stable performance over time, suggesting a plateau.

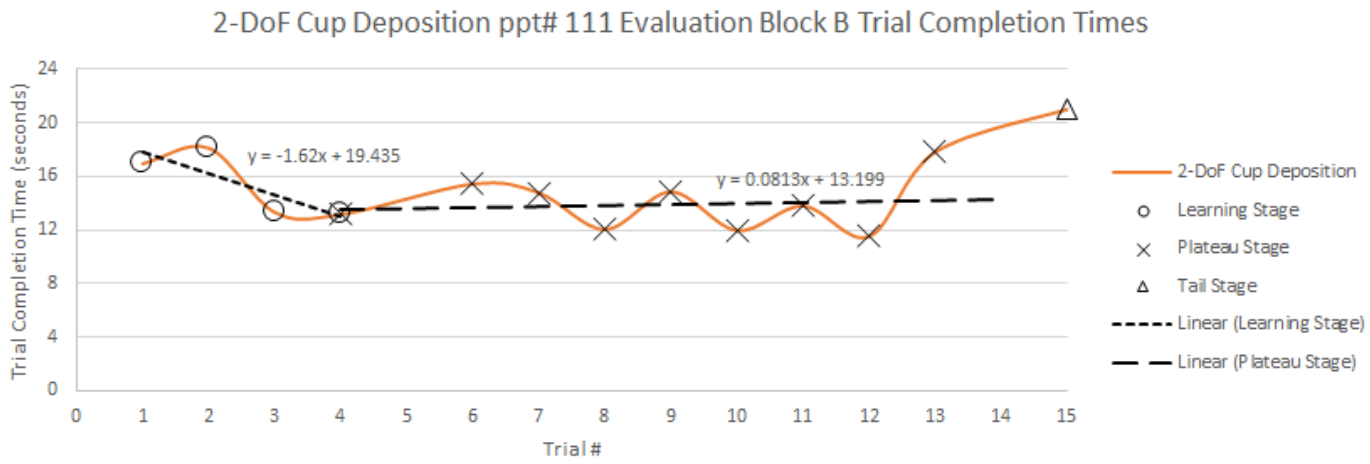

Figure 4-6: Sample participant completion time curve subdivided into test stages, showing negative slope for regression curve fitted to learning stage and flat slope for regression curve fitted to plateau stage. Note that the optimized average plateau region for this test shown here matches closely but not exactly with what could be considered the plateau region data points for this individual participant.

4.5.2 Assessment of Normality

Normality of data was supported for Cup Deposition test completion time and path efficiency averages per participant, including data subdivided into plateau stage data. Normality of data was also supported for TAC test completion time and path efficiency averages per participant, but not for data subdivided by movement type due to the small number of trials involved in calculating these averages (2 repetitions per movement per participant). Normality was not consistently supported for completion rate data for either test, as the ceiling effect resulted in data often clustering around 100% for both tests. Therefore, non-parametric alternatives for assessing test-retest reliability, concurrent validity, and significant differences for the completion rate data sets were selected.

4.5.3 Cup Deposition Test-Retest Reliability

Cup Deposition test average results between evaluation block A and evaluation block B, for metrics of completion time, completion rate and path efficiency, can be seen in Figure 4-7 for both plateau stages and overall test averages; full results and standard deviations can be seen in Table A-2. The ICC values for comparison of test levels and metrics, the associated Standard Error of the Measurement (SEM), and the p-value for the ANOVA repeated measures F-statistic indicating significant differences, can be seen in Table 4-5 (significant p-values are marked with an asterisk, ICC values above 0.60 are identified in bold font). Resnik et al. defined coefficients > 0.80 as “excellent”, from 0.60 to 0.79 as “good”, and <0.60 as “poor” [115]. In their assessment of the reliability of the ACMC test, Lindner et al. denoted ICC values >0.70 as good for research purposes, but only scores >0.90 as being good for clinical

purposes [121], basing this on reporting guidelines by Kottner et al. [122]. Portney and Watkins similarly suggested scores should be over 0.90 to be good for clinical measures [123]. For initial consideration of research applications, the definitions from Resnik et al. are used in the results analysis here.

Table 4-5: Cup Deposition Evaluation Block A and B ICC and ANOVA F-Statistic Results

Test & Stage	**Cup Deposition Test Metric**			
	Completion Time (seconds)		**Path Efficiency**	
1-DoF Test All	ICC=**0.921,** SEM=0.282	F=0.996, p=0.344	ICC=**0.708**, SEM=3.22%	F=0.00943, p=0.925
1-DoF Test Plateau	ICC=**0.885**, SEM=0.329	F=0.211, p=0.966	ICC=**0.663**, SEM=3.50%	F=0.379, p=0.553
2-DoF Test All	ICC=**0.874**, SEM=0.529	F=8.07, p=0.0194*	ICC=**0.682**, SEM=3.28%	F=1.19, p=0.304
2-DoF Test Plateau	ICC=**0.687**, SEM=0.830	F=3.95, p=0.078	ICC=0.462, SEM=4.83%	F=1.05, p=0.333
3-DoF Test All	ICC=**0.772**, SEM=0.811	F=9.23, p=0.0141*	ICC=0.518, SEM=3.07%	F=0.257, p=0.624
3-DoF Test Plateau	ICC=**0.745**, SEM=0.921	F=4.67, p=0.0590	ICC=0.488, SEM=3.43%	F=0.112, p=0.745

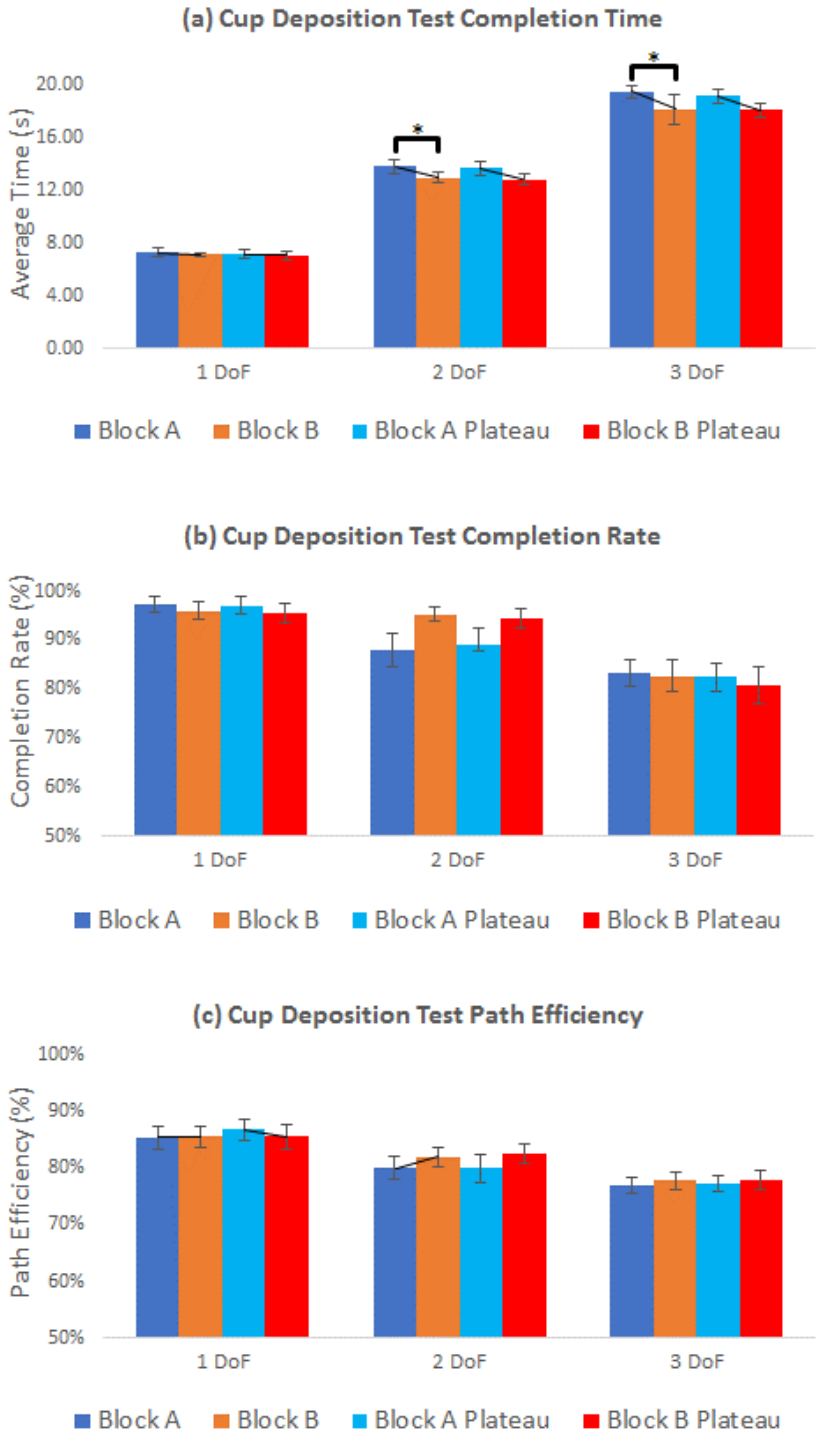

Figure 4-7: Cup Deposition performance metrics between evaluation block A and B: a) Completion Time (lower indicating better performance), b) Completion Rate, and c) Path Efficiency (minimum path length to target over actual path length). (*) indicates significant difference of $p < 0.05$, connecting line indicates ICC of > 0.60. Error bars represent Standard Error of the Mean (SEM).

No significant difference was indicated by the ANOVA results between the plateau-average completion times of block A and block B, supporting the assumption that the plateau stages represented the most meaningful and consistent measures of performance extricable from the test result data. The per-participant plateau stage completion time averages indicated strong test-retest reliability for the 1-DoF test (ICC > 0.80) and moderate test-retest reliability (ICC > 0.60) for 2-DoF and 3-DoF tests. No significant differences between blocks for the path efficiency scores were indicated either; however, in terms of test-retest reliability, only the 1-DoF test showed good reliability for the plateau-average path efficiency scores, whereas the 2-DoF and 3-DoF scores showed weak to poor reliability (ICC > 0.45). This suggested that path efficiency may not have been a consistent measure of a participant's myoelectric control abilities when performing more advanced tasks with multiple DoFs involved, or that participants performing these tasks for the second time tended to improve in path efficiency during the plateau stage such that test-retest reliability was not maintained.

If examining completion time scores averaged over the full test rather than just the plateau test stage, the ANOVA repeated measures results for the 2-DoF and 3-DoF tests suggested significant differences ($p < 0.05$) between block A and block B, despite a high ICC value for both sets. This can be understood as there being a consistent decrease in completion time from evaluation block A to evaluation block B, but this decrease was very minor relative to the variance in completion time scores between participants. This indicated that results were relatively similar for each participant from block A to block B (mean difference of 0.87 seconds and 1.32 for 2-DoF and 3-DoF respectively) if compared to the variance between participants (overall standard deviation of 1.49 and 1.70 for 2-DoF and 3-DoF respectively).

Standard Error of the Measurement values, referred to by Hopkins as the "typical error" of a measure [124], quantify the precision of the scores in the test and provide an index of the expected trial-to-trial noise in the data [115]. The SEM values here ranged from 3 to 5% of their respective metric's average value for the 1-DoF test scores, 4 to 6% of the averages for the 2-DoF test scores, and 4 to 5% of the averages for the 3-DoF test scores, indicating relatively similar levels of score precision across all levels and metrics.

As completion rate results did not meet normality criteria for repeated measures ANOVA and ICC calculation, they were assessed using a non-parametric equivalent: Kendall's W-Statistic, which yields a Coefficient of Concordance (CC) [120]. The results for completion rate data, as well as the results of the

Wilcoxon signed-rank test indicating significance of difference between the data sets, are shown in Table 4-6.

Table 4-6: Cup Deposition Evaluation Block A and B CC and Wilcoxon Z-Statistic Results

Test Level	**Cup Deposition Test Metric**	
	Completion Rate	
1-DoF Test All	CC = 0.02, SEM = 5.02%	Z = -0.707, p = 0.480
1-DoF Test Plateau	CC = 0.02, SEM = 6.40%	Z = -0.412, p = 0.680
2-DoF Test All	CC = 0.37, SEM = 5.02%	Z = -1.781, p = 0.075
2-DoF Test Plateau	CC = 0.267, SEM = 7.53%	Z = -1.667, p =0.096
3-DoF Test All	CC = 0.011, SEM = 8.99%	Z = -0.119, p =0.905
3-DoF Test Plateau	CC = 0.011, SEM = 9.73%	Z = -0.303, p = 0.762

No significant differences were indicated by the Wilcoxon results, indicating the completion rates among all participants do not consistently change between evaluation block A and block B. However, the Coefficient of Concordance values were all poor (<0.40), indicating poor correlation between completion rate performance between the two blocks (within participant) compared to the performance variation between different participants. As many participant completion rate scores were 100% for a number of the tests, it is likely that a ceiling effect hindered this analysis, with insufficient variation among the data points at the upper end to show strong correlation.

4.5.4 Pre-Training and Post-Training TAC Test Differences

For comparison of pre-training and post-training TAC test performance scores, the mean of all participants' test averages for completion time, completion rate and path efficiency at each of the three levels of test can be seen in Figure 4-8; full results and standard deviations can be seen in Table A-3. The difference between pre-training and post-training TAC test performance was assessed by applying the repeated measures ANOVA to the set of all participants' pre-training and post-training per-participant averages; the F-Statistic and P-value significance for completion time and path efficiency are shown in Table 4-7 (significances of $p < 0.05$ indicated by asterisks).

Table 4-7: TAC Test Repeated Measures ANOVA F-Statistic and p-value Results

Test & Stage	**TAC Test Metric**	
	Completion Time	**Path Efficiency**
1-DoF Test	F=5.853, p=0.039*	F=5.556 p=0.043*
2-DoF Test	F=12.311, p=0.0066*	F=9.500, p=0.013*
3-DoF Test	F=8.994, p=0.015*	F=3.064, p=0.11

As completion rate results did not meet normality criteria for the repeated measures ANOVA calculation, they were instead assessed using a non-parametric test for comparing paired data sets, the Wilcoxon signed-rank test; the results are shown in Table 4-8.

Table 4-8: TAC Test Wilcoxon Z-Statistic and p-value Results

Test & Stage	**TAC Test Metric**
	Completion Rate
1-DoF Test	Z=-2.701, p=0.007*
2-DoF Test	Z=-1.973, p=0.049*
3-DoF Test	Z=-1.841, p=0.066

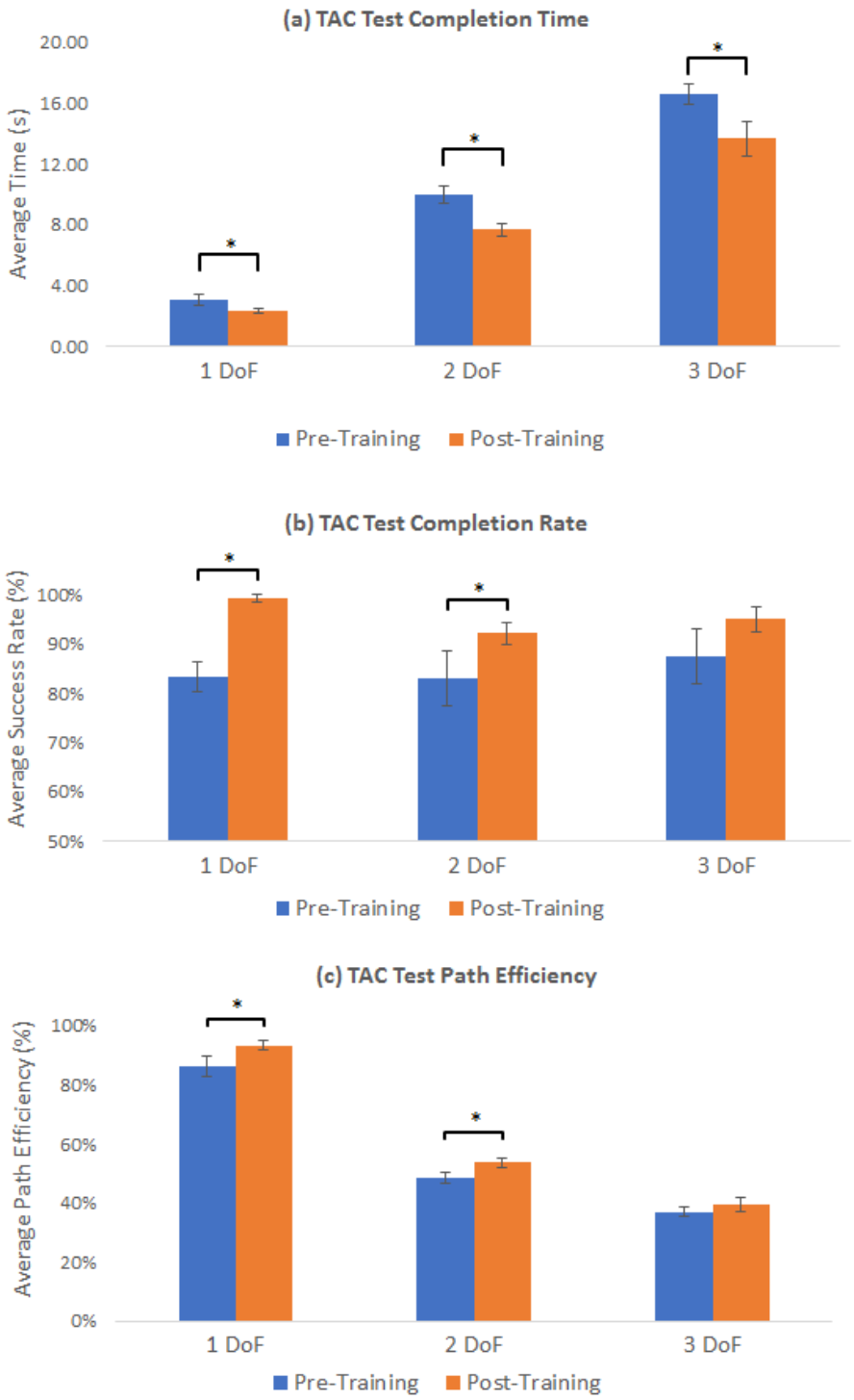

Figure 4-8: TAC test pre-training and post-training performance metrics: a) Completion Time (lower indicating better performance), b) Completion Rate, and c) Path Efficiency (minimum path length to target over actual path length). (*) indicates significant difference of $p < 0.05$

A statistically significant difference was found between the pre-training and post-training TAC test completion, completion rate, and path efficiency test averages for the 1-DoF and 2-DoF tests. For the 3-DoF test, completion time was significantly improved, but not completion rate and path efficiency. Looking at individual data, 7 of the 10 participants showed a decrease in average completion time between pre-training and post-training results for all three tests. The participants that did not match this trend for one of the tests still showed improvements in completion rates, implying that they were now succeeding on previously difficult movements that they had failed at baseline, but taking longer on these than on the movements that were previously successful, thereby increasing their average completion time overall.

Data from the results of the target achievement test was also averaged trial-by-trial in order (i.e. first movement of a test, second movement of a test, etc.) across all participants to examine whether a learning effect was present in the average completion time curve that could influence the difference between the pre-training and post-training performance scores. The TAC test plots of completion time averaged trial-by-trial are shown in Figure 4-9; fitted regression curve slope results are summarized in Table 4-9, as are mean differences between first and last trial completion times of each test. The mean slope of these regression curves was -0.082, a value denoting saturation as it approaches zero, and the mean difference between the first and last trial of a single test was a decrease of 0.78 seconds, indicating minimal training effect across the course of the TAC test itself. This supported the effect of the desktop training protocol as the major contribution to improvements in test scores between the pre-training and post-training TAC tests.

Table 4-9: Slopes of Linear Regression Curves Fitted to TAC Test Trial-by-Trial Average Completion Times

TAC Test Level		Fitted Regression Curve Slope	Change from First Trial to Last Trial (seconds)	Change from First Half of Test to Second Half of Test (seconds)
1-DoF:	Pre-Training	-0.0176	-0.517	-0.0983
	Post-Training	-0.0300	0.0750	-0.161
2-DoF:	Pre-Training	-0.0141	-3.124	-0.227
	Post-Training	-0.0206	0.598	-0.184
3-DoF:	Pre-Training	-0.355	-8.769	-2.147
	Post-Training	-0.0599	7.070	-0.651
Average	Pre-Training	-0.129	-4.137	-0.824
	Post-Training	-0.0368	2.581	-0.332
	Overall	**-0.0828**	**-0.778**	**-0.578**

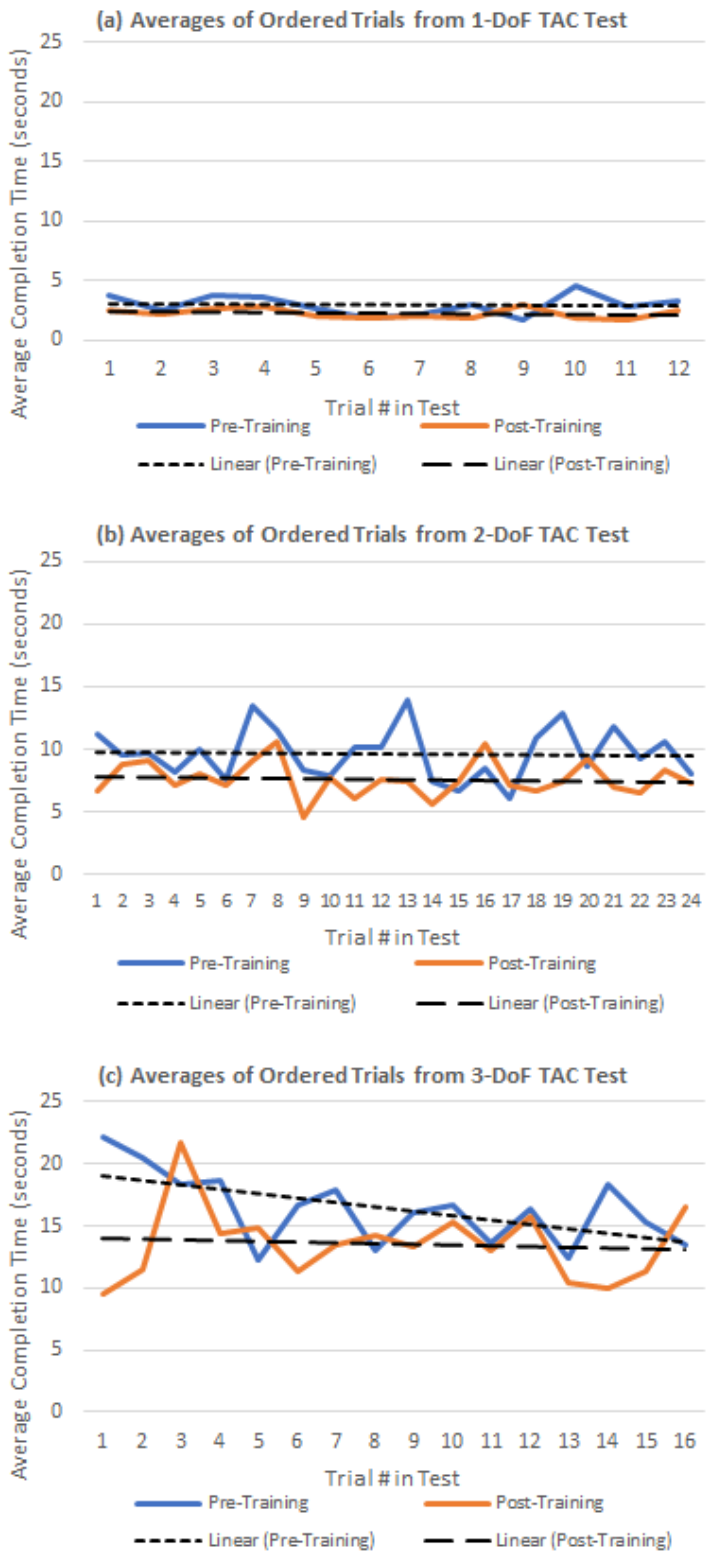

Figure 4-9: Pre-training and post-training trial completion times, averaged trial-by-trial in the order performed, with regression curves fitted for the (a) 1-DoF TAC test, (b) 2-DoF TAC test, and (c) 3-DoF TAC test.

4.5.5 Cup Deposition to TAC Test Correlation

Correlation between participant TAC test scores and Cup Deposition scores was illustrated by fitting a regression line, as in Figure 4-10 for average trial completion times, Figure 4-11 for average trial completion rates, and Figure 4-12 for average trial path efficiencies. Cup Deposition scores were taken as the mean of block A and block B plateau stage averages for each participant, as the differences between plateau stages were established to be non-significant in the analysis in section 4.5.3; average scores per participant were used since results from individual trials would not able to be compared due to the different number of trials per test between the TAC test and the Cup Deposition test.

Pearson correlation coefficients generated from the SPSS Pearson bivariate correlation analysis are shown in Table 4-10. Using the definition of Resnik et al., we defined coefficients > 0.50 as "large", from 0.50 to 0.30 as "moderate", and <0.30 as "small" [115].

Table 4-10: Cup Deposition and TAC Test Metric Pearson Correlation

Test Level	**Cup Deposition and TAC Test Metric**	
	Completion Time	**Path Efficiency**
1-DoF Test	r = 0.548	r = 0.391
2-DoF Test	r = 0.346	r = 0.142
3-DoF Test	r = 0.570	r = 0.498

Moderate to large correlation was supported for the TAC test and Cup Deposition completion time scores, with the 3-DoF test scores showing the largest correlation (r = 0.570). Path efficiency correlation showed a similar pattern, suggesting at least moderate correlation for the 3-DoF test (r = 0.498). Overall, 3-DoF test scores indicated higher correlation than the 1-DoF and 2-DoF tests, possibly suggesting that 1-DoF and 2-DoF Cup Deposition tests are too simple to clearly reflect the differences in ability among different participants that would be shown in more difficult tests. This was also supported by the relatively lower standard error of the measurement value and smaller standard deviation for the sets of participant scores for the 1-DoF and 2-DoF Cup Deposition tests (see Table 4-5 and Table 4-6, and Table A-2 in Appendix A).

For the completion rate data that did not meet normality requirements, Spearman's rho correlation coefficients are shown in Table 4-11.

Table 4-11: Cup Deposition and TAC Test Metric Spearman Correlation

Test Level	**Cup Deposition and TAC Test Metric**
	Completion Rate
1-DoF Test	$\rho = -0.302$
2-DoF Test	$\rho = 0.631$
3-DoF Test	$\rho = -0.014$

Spearman correlation values between TAC test completion rate and Cup Deposition completion rate range from moderate to small to negative values, suggesting poor correlation overall, partially due to the ceiling effect resulting in many data points clustered around 100%. As completion rates showed poor test-retest reliability as indicated by the Coefficient of Concordance calculation in section 4.5.3, this suggested that, in contrast to completion time and path efficiency, completion rate and the occurrence of failed trials in the Cup Deposition tests may have occurred mostly randomly and not related strongly to the skill of a given participant.

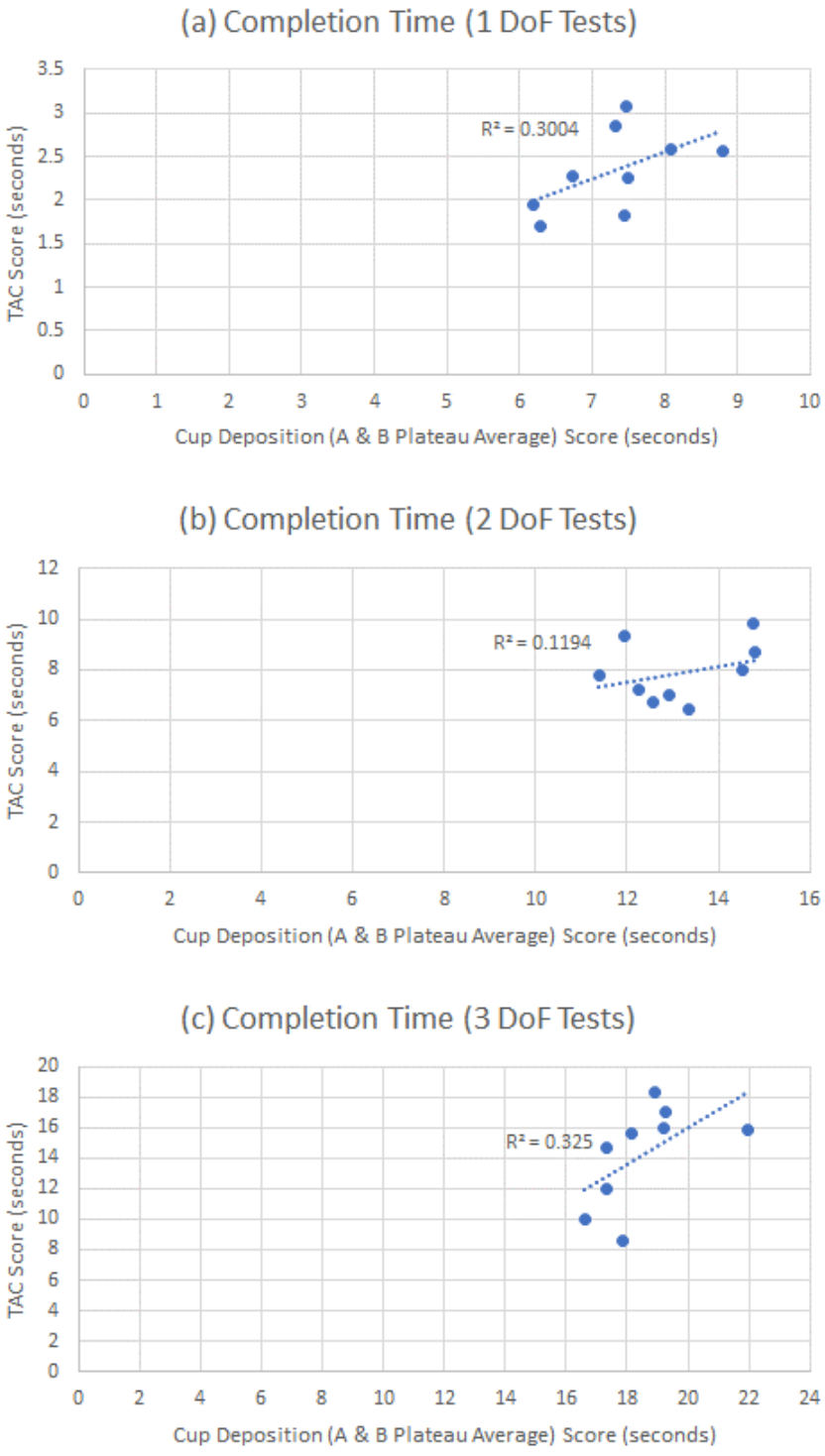

Figure 4-10: Linear regression curve between Cup Deposition and TAC test Completion Time Scores for (a) 1-DoF Tests, (b) 2-DoF Tests, (c) 3-DoF Tests

Figure 4-11: Linear regression curve between Cup Deposition and TAC test Path Efficiency Scores for (a) 1-DoF Tests, (b) 2-DoF Tests, (c) 3-DoF Tests

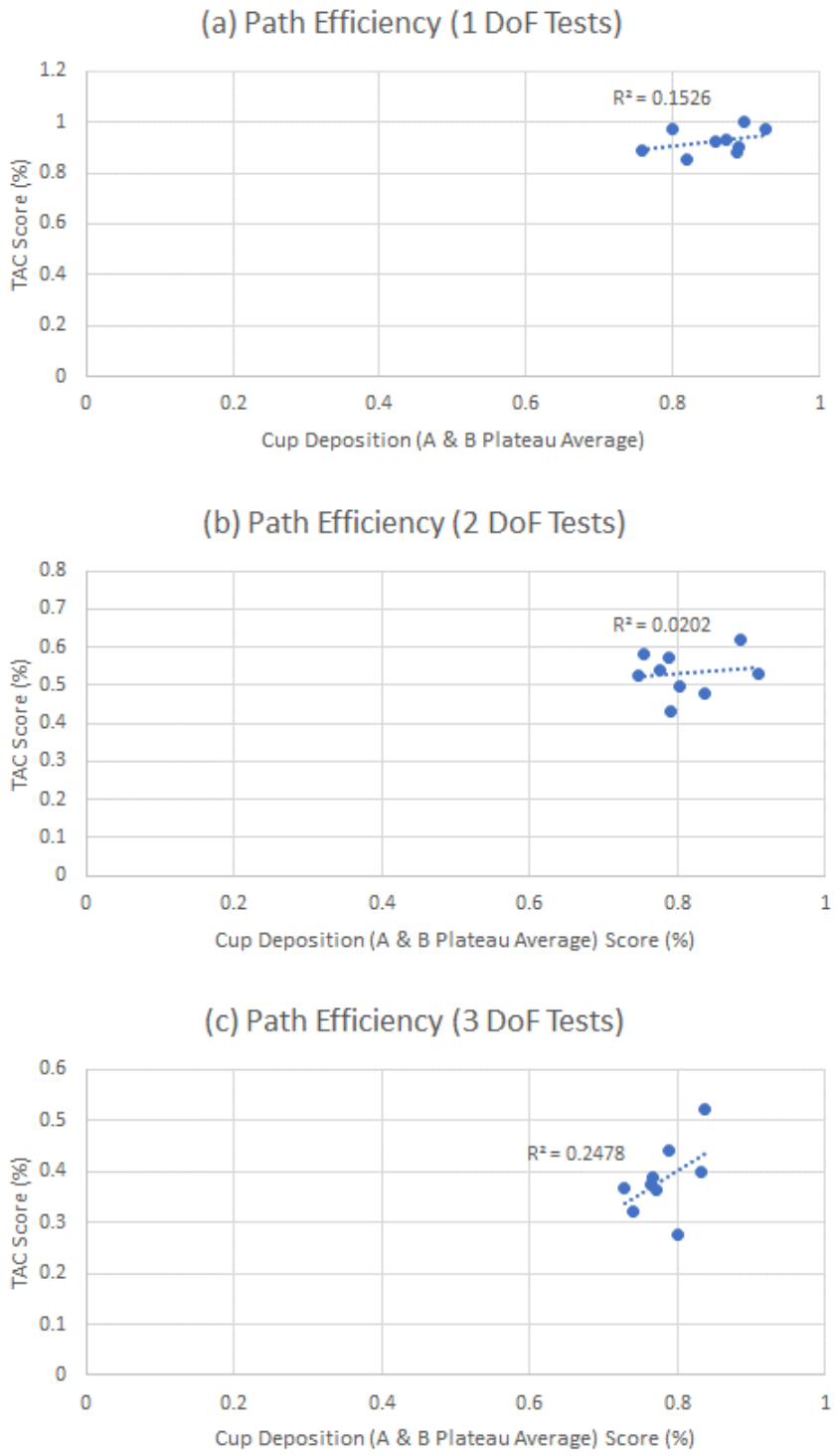

Figure 4-12: Linear regression curve between Cup Deposition and TAC test Completion Rate Scores for (a) 1-DoF Tests, (b) 2-DoF Tests, (c) 3-DoF Tests

4.5.6 Usability Survey Results

Usability survey results from all participants are summarized in Table 4-12 and Figure 4-13.

Table 4-12: Usability Survey Visual Analogue Scale Response Averages

Attribute		Average VAS Score
Intuitiveness		75%
Reliability		65%
Effectiveness	**CD 1-DoF**	87%
	CD 2-DoF	75%
	CD 3-DoF	66%
	TAC Test	79%

The VAS result average values suggested that participants found the pattern recognition-based control system implemented in this study to be fairly intuitive, but relatively less reliable compared to its intuitiveness. Effectiveness was ranked higher for the simpler Cup Deposition tests with less DoFs required. Effectiveness on the TAC Test rated higher than the 2-DoF and 3-DoF Cup Deposition tests, possibly because the TAC test itself incorporated all three DoFs in varying combinations at different levels of the test; another factor may be that testing in a virtual environment removes potential additional influences on control effectiveness such as inertia, servo lag, obstructed field of vision, slippage, etc.

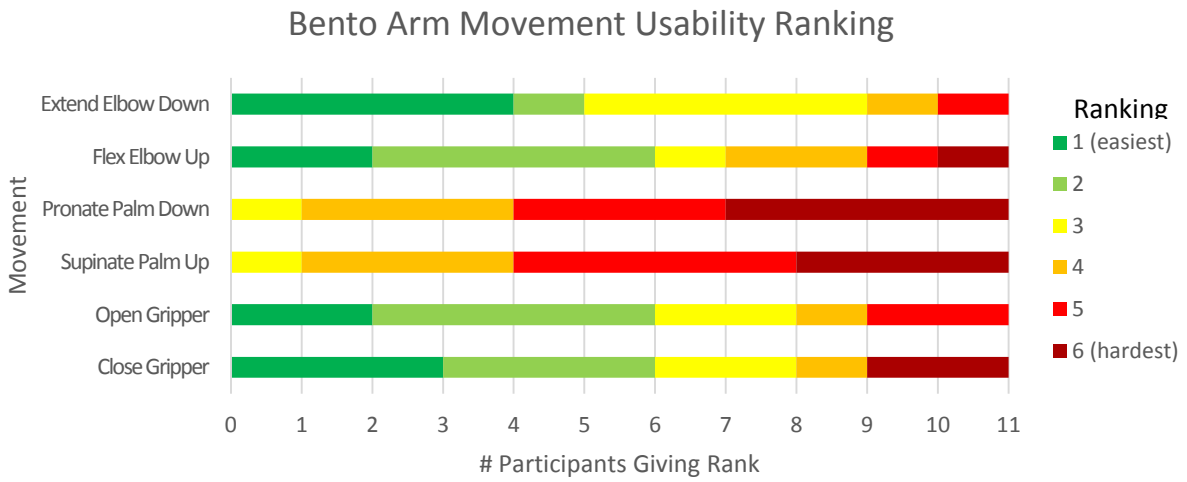

Figure 4-13: Participant rankings of Bento Arm movement usability. Each coloured bar segment represents the total number of participants giving a specific rank to a specific movement. Colours associated with higher rank number (from 1 to 6) indicate the movement is more difficult to use.

Usability ranking by movement indicated that the most frequently rated difficult movements for participants to control were supination and pronation. Survey responses indicated these were readily mixed up with both elbow flexion/extension movements and gripper open/close movements. Elbow extension and, to a lesser extent, elbow flexion were the movements most frequently ranked as easiest to move; open and close gripper were variously ranked as some of the easiest movements by some participants and some of the hardest by others. These results suggested that movements controlled primarily by two antagonist muscles (such as the biceps and triceps) were easiest to distinguish in terms of EMG signals, whereas those controlled by a combination of numerous muscles (pronation and supination) produced more nuanced EMG signal patterns that were more difficult to distinguish and more frequently confused with the signal patterns of other movements.

4.6 Discussion

4.6.1 Training Effect Discussion

Many researchers have focused on developing tasks in virtual environments to improve performance of myoelectric prosthetic control [6][40]. However, these virtual environments do not capture specific difficulties of controlling an actual prosthetic device, i.e., mechanical variability, and factors involved in the manipulation of physical objects. In this work, a training protocol was developed using a desktop robotic training tool to fill this gap. A structured training protocol using a desktop system applicable to both able-bodied participants and participants with amputations was assessed over a single session. Results showed that using a desktop robotic arm in the developed protocol indeed improved multi-DoF control, as measured by performance on the TAC test. Results for the 1-DoF and 2-DoF TAC tests, which required the user to perform simpler movements than the 3-DoF test, demonstrated significantly improved performance with regards to task completion time, completion rate, and path efficiency. Despite finding improvement in completion time performance for 3-DoF tests, results for completion rate and path efficiency did not reach statistically significant levels, but were promising. The fact that the TAC test results for completion rate and path efficiency did not show significant post-training improvement for the 3-DoF tests may be explained by the limited time participants had to practice control of the robotic arm on tasks that required all three DoFs, as these only comprised the latter third of the training protocol and the desktop-evaluation. This may also reflect differences in strategies for improvement among different participants; while some participants may have aimed for more efficient movements and to complete the difficult movements they failed in the pre-training test, others may just have focused primarily on improving their time on the movements with which they had already succeeded. Overall, this work serves as a preliminary evidence to proceed with examining training effects using this protocol in the targeted population of upper limb myoelectric prosthesis users.

Looking at similar work in the literature, previous quantifiable assessments of the effects of user training on myoelectric prosthetic control are limited. Takeuchi et al. developed and assessed a virtual training system for myoelectric control using conventional two-electrode direct control for a single DoF, involving manipulation of a virtual object with moderation of grip so as not to “break” it; their results showed significant improvement over the course of five days of training sessions [125]. Bouwsema et al. performed a similar assessment, using three different training platforms for able-bodied participants: a virtual hand, a desktop-mounted robotic gripper, and a bypass-mounted prosthesis [98], finding

comparable improvements in myoelectric control ability with training with all three. Both of these studies, though, only assessed training with simple 1-DoF direct conventional myoelectric control.

More recently, Powell et al. assessed the effect of training pattern recognition-based myoelectric control over the course of a two-week training period, using virtual evaluation based on TAC test metrics [7]. Four participants with transradial amputations completed daily one-hour training sessions controlling a virtual arm with biofeedback. Results showed significant improvement in both completion time and completion rate scores, though training and evaluation in this study were performed on the same platform and were highly similar. The authors note that one advantage of functional user-training with a physical prosthesis is the added "realism of maintaining control of an object versus dropping it" [7], a benefit shared by training and evaluation systems with a desktop-mounted robotic arm as well. Although nine movements were trained, this experiment only tested single-DoF individual movements at a time, not combined movements as in the 2-DoF and 3-DoF level tests here.

Hargrove et al. performed an assessment of training with prosthesis users that included TAC test pre-training and post-training performance scores, although in this case the intervention consisted of six weeks of home use with a socket-mounted prosthesis rather than a number of sessions with a designated training protocol [94]. The improvements shown in these experiments with training on virtual and wearable prostheses are consistent with the findings of our study: that user performance with pattern recognition-based myoelectric control was also significantly improved by training on a desktop-mounted system. The work here complements the study by Hargrove et al. by examining training effect as measured by performance on the TAC test, but with training performed on an intermediate platform (a desktop-mounted robotic arm) instead of an end-user platform (a socket-mounted custom-fitted wearable prosthesis).

Unlike the tasks in virtual environments in much of the previous work in literature, the training tasks developed in this protocol were designed to integrate various tasks that a prosthesis user would be exposed to in a clinical setting; grasping, manipulating, and moving actual objects. However, these integrated tasks were limited to the reaching range and workspace envelope of the desktop robotic arm; the validity of applying results from this set-up to activities requiring a full range of motion on a wearable prosthesis will need to be further explored. Further limitations of this part of the study include the use of only able-bodied participants, meaning future studies will need to verify the results are similarly applicable to participants with amputations.

With regards to potential refinement of the experiment, assessment of the training effect here comprised a quasi-experimental design rather than a randomized experiment including a control group. Running a control experiment, in which participants perform two TAC tests at different times but no desktop training activity, would be beneficial to establishing performance differences as the result of the training and not a learning effect in the test itself. Although this point was partially addressed in the TAC test completion time regression curve analysis, results from control participants could further substantiate that the differences here were due solely to the desktop training. Other future refinements to the training protocol may include multiple training and testing sessions to investigate the ability of the users to maintain improved performance (i.e. learning retention), and to investigate if more extensive desktop training results in greater improvements, or whether performance improvement slows after a certain amount of time or number of sessions (i.e. training plateau).

4.6.2 Desktop Evaluation Validity Discussion

Tests in virtual environments used for assessment of myoelectric control do not capture various aspects of controlling an actual prosthetic device, but evaluating a fitted, socket-mounted final prosthetic device is often a high-burden intervention for early control research. In this work, a novel evaluation task, the Cup Deposition test, was developed using a desktop-mounted robotic device as an intermediate platform. For this test, participants performing a simple object manipulation with myoelectric control were assessed on their completion time, completion rate and path efficiency. Results showed that, as an evaluation tool, the task possessed moderate-to-high reliability for completion time results, and moderate-to-low reliability for path efficiency; sufficient for research purposes, but insufficient for clinical applications if applying the higher thresholds of Kottner et al. [122] or Portney and Watkins [123].

Compared with the Target Achievement Control test, the task demonstrated moderate to large concurrent validity for completion time results, and poor to moderate concurrent validity for path efficiency with the 3-DoF test demonstrating the highest correlation for both metrics. Task completion rate data demonstrated non-normality and poor test-retest reliability, as well as poor correlation with TAC test results. Overall, these results indicate completion time as the most promising metric from the Cup Deposition test in terms of reliability and concurrent validity; however, while adequate for research purposes, further improvements may need to be made to meet standards for clinical application. Path efficiency data may present some valid information in addition to this, but completion rate data from the test does not appear to convey meaningful evaluation information.

Validity for assessments of prosthetic devices and control is challenging to establish in general, and has been the focus of much research and working groups such as the Upper Limb Prosthetic Outcome Measures (ULPOM) Group [83]. Resnik et al. performed a systematic review of measures of impairment and activity limitation for persons with upper limb trauma and amputation, but concluded that only a few measures could be recommended as fully validated [92]. Most of the validated assessments were self-reported measures, and of the recommended performance measures, the majority require subjective rater assessment; all measures required a fully-fitted wearable prosthesis for the participant, ruling out intermediate platforms such as simulated prostheses or desktop-mounted devices. One of the fully validated performance measures, the Box and Blocks test [114], has been implemented in a modified format using a desktop-mounted robotic arm, the Myoelectric Training Tool [69]. However, this version of the test requires a minimum of 4 active DoFs in the device (gripper open/close, wrist

flexion/extension, elbow flexion/extension, humeral rotation) to perform, while not incorporating the more common wrist supination/pronation movement; furthermore, it requires the participant to perform non-automated joystick control of humeral rotation, confounding an assessment of participant myoelectric control. Aside from the Myoelectric Training Tool and the Bento Arm, desktop-mounted robotic devices used for evaluation and training are limited to robotic arms with few DoFs and not used to manipulate objects [8][98].

The novel evaluation task developed in this work fulfills the niche of an intermediate research and training platform for prosthetic control, with no fitting or mounting requirements, the ability to be used by both able-bodied and individuals with amputation, and the ability to provide quantitative data on the performance of control systems on simple functional tasks in a consistent test environment for varying numbers of DoFs. Compared to virtual assessments, it allows manipulation of a variety of objects, and includes physical factors involved in prosthetic operation such as inertia, friction, and object weight. From qualitative comments, participants favoured the desktop-mounted robotic arm evaluations, as virtual assessment was perceived to be more sensitive and prone to unintentional movements, less satisfying to complete, and less intuitive to embody.

Some notable limitations of this part of the study include the use of only a relatively small number of able-bodied participants, and therefore further verification is needed through testing of prosthesis users. Other limitations include effects of the two block, three-level evaluation structure of the Cup Deposition test that was used for validation purposes; it is for example possible that, in moving from the lower-levels to the higher levels of the test, the participants may have acquired practice that influenced their performance on the higher level tests and in the second evaluation block.

Relating to the motivating questions of this thesis, the primary future direction of this research should include assessing other forms of validity of the test, and making modifications if it proves unsatisfactory in important psychometric properties. Concurrent validity should be assessed in comparison to a better-validated test than the TAC test, ideally incorporating validated clinical evaluations using a wearable prosthesis such as AMULA, ACMC or Box and Blocks. These types of evaluations should also be used for further assessing and establishing the training effect of the desktop training tool on myoelectric control performance. Other psychometric properties that could be assessed for validation of the Cup Deposition test include internal consistency (having a greater number of trials and comparing subdivided test results), predictive validity (correlation with performance results of a

validated test performed at a later time), and responsiveness (the ability of the test to detect change in performance after an intervention, such as a training session, has been administered) [92].

Although only one variant of pattern recognition-based control was used in this study, the test could be applied to comparison of a variety of different myoelectric control strategies, including conventional direct control, variations of pattern recognition with different controllers or post-classification operations, or control systems that incorporate machine learning algorithms such as reinforcement learning. The training and evaluation protocol developed here could be used to assess differences in participant learning rates and performance effects of training between different myoelectric control strategies, indicating whether some control strategies may be easier to learn than others and whether some may benefit more extensively from user training.

Other future refinements to the evaluation task may include modifications to the number of trials per test: increasing the number of trials for the more difficult 2-DoF and 3-DoF test levels that showed high variance in results, while decreasing the number of trials for the highly consistent 1-DoF level of testing. Bento Arm velocity could be normalized against the required angular displacement for each DoF, meaning all DoF movements would in theory contribute equally to task completion time scores. Although participant wrist flexion/extension was used to control the Bento Arm gripper in this study due to the clarity of the EMG patterns for these movements, some participants commented that they found this to be unintuitive; the input movements for gripper control may therefore be replaced with more intuitive hand open/close movements in future iterations.

Overall, refinements and future work involving the Cup Deposition test should have the general goal of making it a more useful, robust and representative assessment of prosthetic myoelectric control, in a way that is meaningful to prosthesis users. To this end, validating the Cup Deposition test in comparison to established clinical prosthetic tests, involving a wearable socket-mounted prosthesis and the performance of activities of daily living, would build upon the work done here developing this intermediate-platform evaluation.

5.0 Conclusion

The major contributions and conclusions of this thesis are summarized in this chapter. The broader impact of the questions investigated here within the field of upper limb prosthetic research is considered, and future work in the area of training and evaluating myoelectric control strategies is discussed.

5.1 Study Conclusions

For persons with amputations, the adoption of powered myoelectric prostheses and their ability to improve quality of life is hindered by the difficulty of controlling multiple DoFs with a limited number of input signals. Different myoelectric control strategies have been developed to address this challenge, but research evaluating myoelectric control strategies in a wearable prosthesis with actual prosthesis users is limited. Control is therefore more commonly evaluated using offline evaluations and virtual reality-based tests. Desktop-mounted robotic devices offer a potential intermediate platform with less intensive requirements of a full socket fitting, but more applicability to functional prosthetic ability.

The main objective of this thesis was to develop and assess a training protocol and evaluation task for pattern recognition-based myoelectric control using a desktop-mounted robotic arm. A literature review was conducted to better understand the current state of upper limb prosthesis myoelectric control strategies, challenges faced in development, and gaps in the control evaluation methodology, as well as the most recent developments in pattern recognition user training protocols.

By integrating open-source software (BioPatRec) into existing robotic hardware and software (the Bento Arm and brachI/Oplexus), a desktop-mounted robotic arm was configured to be operated with PR-based myoelectric control. Based on the information acquired in the literature review and input from an occupational therapist, a protocol and standardized task set-up for training and evaluating myoelectric control with this desktop-mounted robotic arm was developed. This was assessed in an experimental study with 10 able-bodied participants, which involved training participants in myoelectric control and measuring their performance in a pre-training and post-training evaluation with a previously-established virtual test (the TAC test), and two successive blocks of post-training evaluation with a novel desktop-based evaluation (the Cup Deposition test). Results indicated that the training protocol improved myoelectric control significantly as measured by performance on the TAC test. Application of the novel desktop evaluation task indicated good reliability and concurrent validity with the virtual test for research purposes; however, for clinical application further development of the task is required to reach acceptable levels in these validations.

5.2 Impact on the Field

The work developed here is poised to fulfill an important niche in the field of myoelectric prosthetic research where gaps currently exist. The desktop training protocol could be used as a research intervention to determine how training affects improvement and learning rates across different myoelectric control strategies. It could also be used in a clinical application, allowing patients to practice a variety of myoelectric control strategies such as pattern recognition in order to determine which system is best suited for them when they are ready to be fitted with a full socket and prosthesis. The desktop evaluation can be used in myoelectric control research to assess control strategies involving nearly any combination of DoFs, and can be used with both able-bodied participants and participants with amputations. Since all the software used (brachI/Oplexus and BioPatRec) is open-source and most of the hardware is either open-source, 3D-printed or off-the-shelf, this desktop training and evaluation system or specific elements of it can be easily used by other researchers in the field, or further developed and improved upon as desired. Overall, exploring and understanding different approaches to evaluating myoelectric control strategies will improve our ability to further meaningful research and development in this field.

5.3 Future Work

Future work in the field could build on the work presented here in two primary ways. First, the training protocol could be improved and refined, including more rigorous assessment of the training and learning effects across VR, desktop and other platforms in both able-bodied participants and participants with amputations. This could then be used to explore training intervention effects under different conditions, for example with different myoelectric control strategies such as direct control, pattern recognition variations, and systems incorporating reinforcement learning. Secondly, the desktop evaluation task could be refined and further validated. This includes both validation of additional psychometric properties, and setting up comparisons with myoelectric control evaluations on other platforms, looking in particular at correlation with wearable socket-mounted prostheses.

In general, even if full socket-mounted prosthesis-based evaluation is not viable in some situations, research into myoelectric control should move away from offline evaluation towards more intermediate platforms such as advanced simulations or desktop-mounted robotic devices, which will give researchers more insight earlier in the development process into how developments in myoelectric control strategy can truly benefit persons with amputations in terms of functional capacity in their daily lives.

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Appendix A: Additional Tables and Figures

Table A-1: Target Achievement Control Test Movement Combinations by Test DoF

TAC Test Level	Combined Movement #	Movement Incorporated		
1-DoF	1	Open Hand		
	2	Close Hand		
	3	Pronation		
	4	Supination		
	5	Flex Elbow		
	6	Extend Elbow		
2-DoF	1	Open Hand	Pronation	
	2	Open Hand	Supination	
	3	Open Hand	Flex Elbow	
	4	Open Hand	Extend Elbow	
	5	Close Hand	Pronation	
	6	Close Hand	Supination	
	7	Close Hand	Flex Elbow	
	8	Close Hand	Extend Elbow	
	9	Pronation	Flex Elbow	
	10	Pronation	Extend Elbow	
	11	Pronation	Flex Elbow	
	12	Pronation	Extend Elbow	
3-DoF	1	Open Hand	Pronation	Flex Elbow
	2	Open Hand	Pronation	Extend Elbow
	3	Open Hand	Supination	Flex Elbow
	4	Open Hand	Supination	Extend Elbow
	5	Close Hand	Pronation	Flex Elbow
	6	Close Hand	Pronation	Extend Elbow
	7	Close Hand	Supination	Flex Elbow
	8	Close Hand	Supination	Extend Elbow

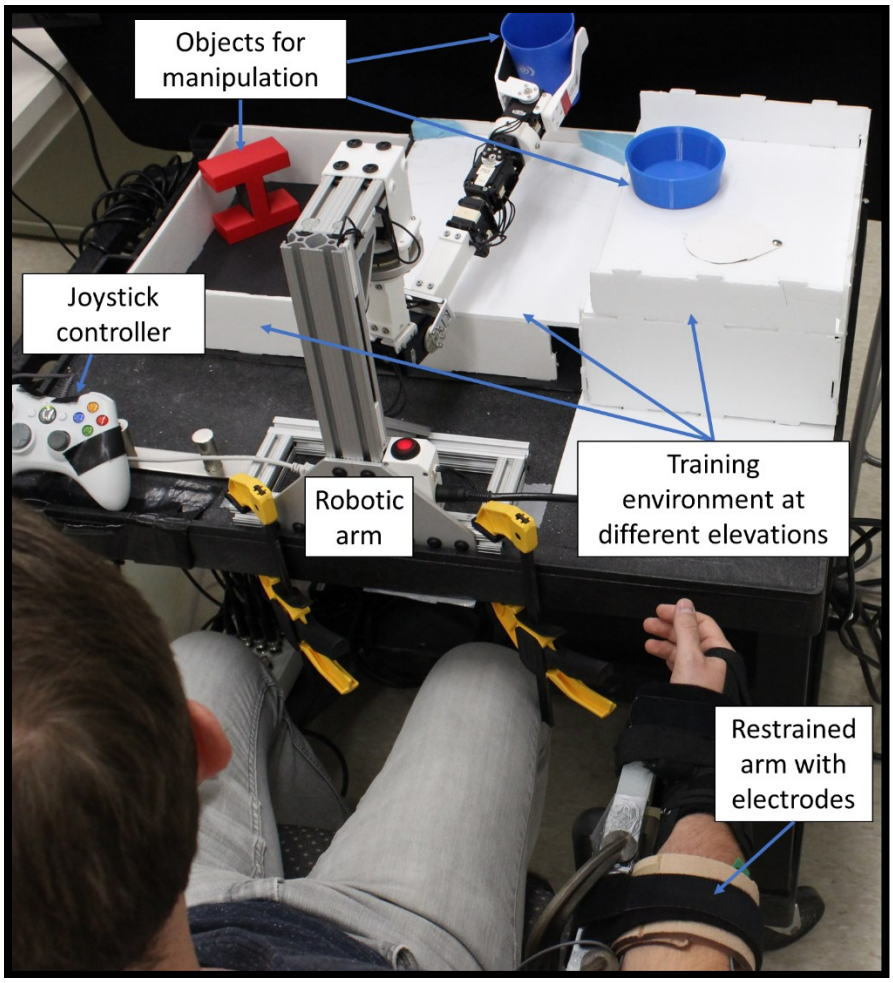

Figure A-1: Participant seated in front of desktop-mounted robotic arm myoelectric control training environment, showing three distinct surface areas at different elevation levels from left to right, items for manipulation, joystick controller, and participant with electrodes attached

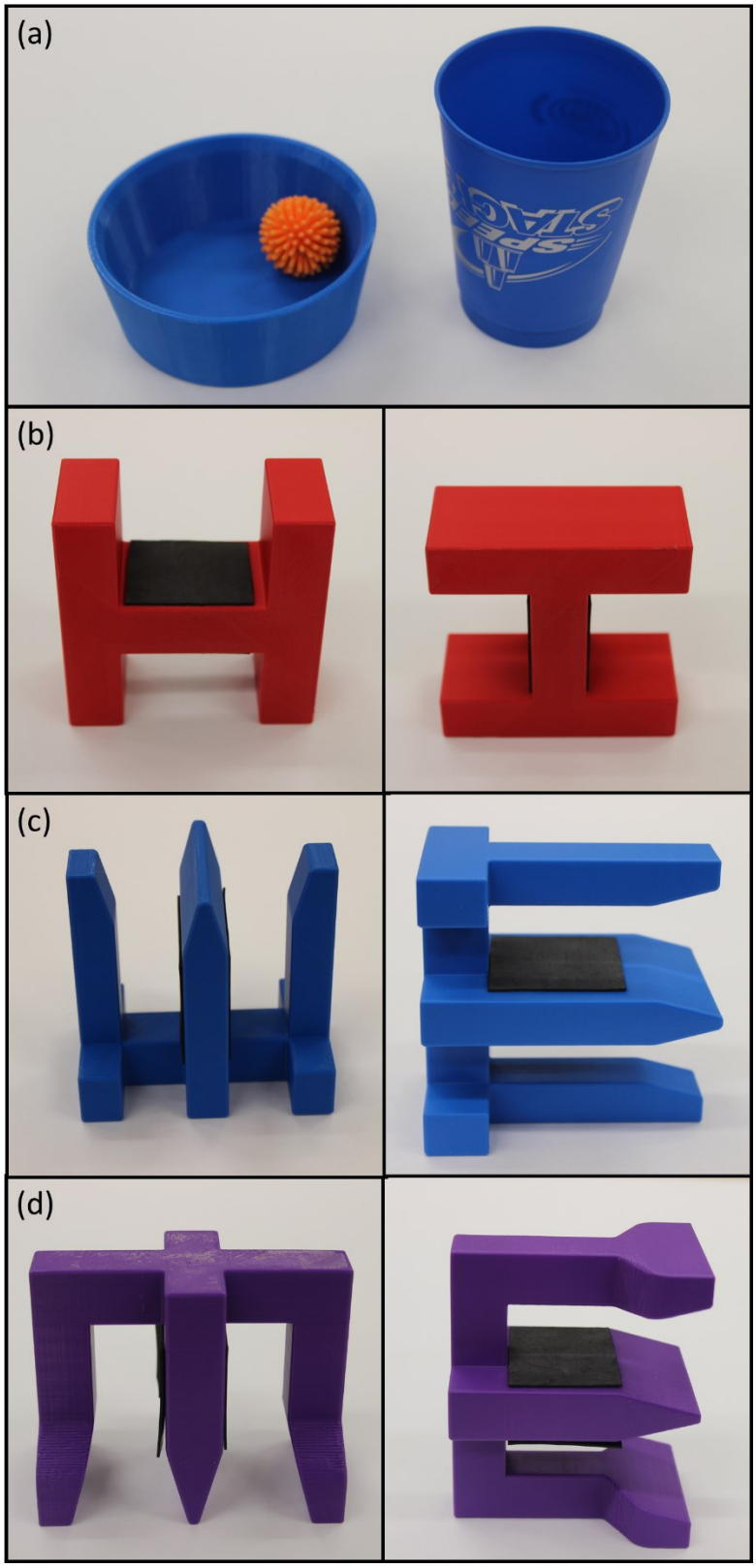

Figure A-2: Desktop training protocol objects for manipulation: a) cup, bowl and ball, b) H-block, c) W-block, and d) M-block

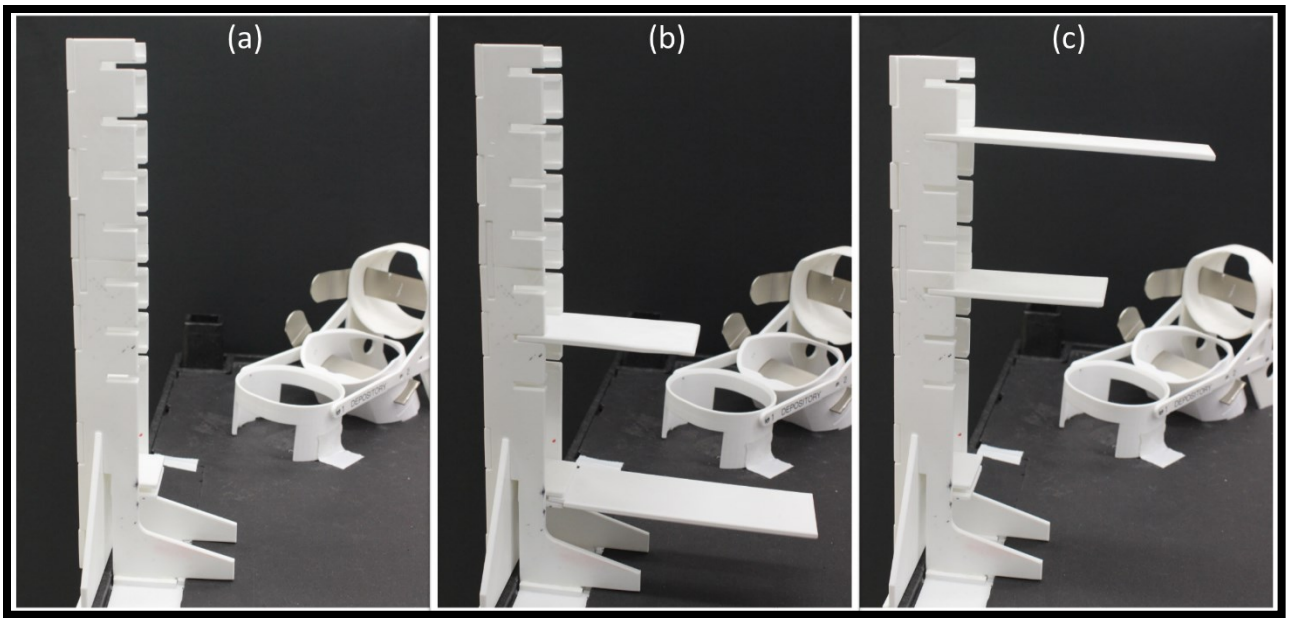

Figure A-3: Cup Deposition test plank configuration, for a) 1-DoF test, b) 2-DoF test, and c) 3-DoF test

Table A-2: Cup Deposition Test Results and Standard Deviation

Test & Stage	Cup Deposition Test Metric					
	Completion Time (seconds) & Standard Deviation		Completion Rate & Standard Deviation		Path Efficiency & Standard Deviation	
	Block A	Block B	Block A	Block B	Block A	Block B
1-DoF Test All	7.32, σ = 0.950	7.15, σ = 1.095	97.3%, σ = 4.66%	96.0%, σ = 5.62%	85.3%, σ = 5.97%	85.5%, σ = 6.27%
1-DoF Test Plateau	7.19, σ = 0.882	7.10, σ = 1.098	97.0%, σ = 6.75%	95.5% σ = 6.43%	86.7%, σ = 5.52%	85.5%, σ = 6.75%
2-DoF Test All	13.87, σ =1.636	13.00, σ =1.256	88.0%, σ = 10.80%	95.3%, σ = 4.50%	80.0%, σ = 6.51%	82.0%, σ = 5.17%
2-DoF Test Plateau	13.74, σ = 1.674	12.85, σ = 1.182	89.1%, σ = 10.32%	94.5%, σ = 6.36%	79.9%, σ = 7.79%	82.4%, σ = 5.22%
3-DoF Test All	19.52, σ = 1.496	18.20, σ = 1.696	83.3%, σ = 8.46%	82.7%, σ = 10.04%	82.7%, σ = 7.96%	80.9%, σ = 11.70%
3-DoF Test Plateau	19.23, σ = 1.723	18.13, σ = 1.840	76.9%, σ = 4.35%	77.7%, σ = 4.71%	77.3%, σ = 4.16%	77.9%, σ = 5.58%

Table A-3: Target Achievement Control Test Results and Standard Deviation

Test & Stage	TAC Test Metric					
	Completion Time (seconds) & Standard Deviation		Completion Rate & Standard Deviation		Path Efficiency & Standard Deviation	
	Pre-training	Post-training	Pre-training	Post-training	Pre-training	Post-training
1-DoF Movement Test	3.035, σ = 1.172	2.270, σ = 0.496	83.3%, σ = 9.62%	99.2% σ = 2.64%	86.3%, σ = 10.97%	93.3%, σ = 5.09%
2-DoF Movement Test	9.989, σ = 1.681	7.677, σ = 1.301	82.9%, σ = 17.51%	92.1%, σ = 6.93%	87.5%, σ = 17.43%	95.0%, σ = 8.23%
3-DoF Movement Test	16.582, σ = 2.147	13.662, σ = 3.600	48.6%, σ = 5.48%	53.6%, σ = 5.66%	37.0%, σ = 5.73%	39.6%, σ = 7.51%

Appendix B: Additional Bento Arm Data Logging Information

The value of the electric load required by the Bento Arm gripper servo was recorded by the automatic logging function as a means of approximately assessing the consistency of the grip force being applied by the user through the Bento Arm during the evaluation. This load value was correlated with the force applied by the gripper using the BLINC lab instrumented mechanical cup, a cylindrical device with perpendicular force gages integrated to allow it to measure the gripping force applied to it. Data was acquired by tightening the Bento Arm gripper about the cylinder in very small increments up until the maximum load, then likewise releasing it in small increments, allowing the collection of data logs of load and force for both dynamic and static situations. Results indicated that, although mismatched for changing load, static load consistently strongly correlated (r = 0.973) with force applied across a wide range, as illustrated in the regression curve shown in Figure B-1. Hence, for constant levels of force, the logged load data can indicate when in a given trial participants were applying maximum force, steady holding force, no force, or wavering in force applied.

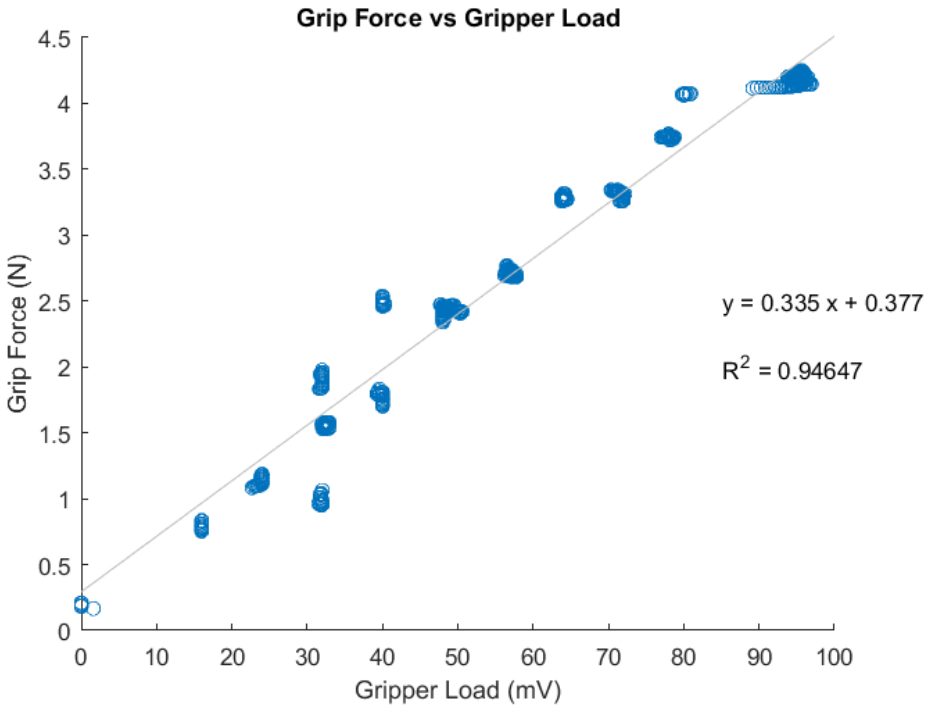

Figure B-1: Static grip force as measured by the instrumented cup vs Bento Arm gripper load

Appendix C: Usability Survey

Usability Survey

Intuitiveness

Intuitiveness is defined as how easy it was to learn how to use the controller.

How easy was the control mode to learn?
Mark with an "x" on the line below.

Very easy **Very difficult**

Effectiveness

Effectiveness is defined as how well the controller was able to perform the task.

How well did the control mode perform the 1-DoF cup deposition task?
Mark with an "x" on the line below.

Very poorly **Exceptionally well**

How well did the control mode perform the 2-DoF cup deposition task?
Mark with an "x" on the line below.

Very poorly **Exceptionally well**

How well did the control mode perform the 3-DoF cup deposition task?
Mark with an "x" on the line below.

Very poorly **Exceptionally well**

How well did the control mode perform the clothespin relocation task?
Mark with an "x" on the line below.

Very poorly **Exceptionally well**

How well did the control mode perform the Target Achievement Control task?
Mark with an "x" on the line below.

Very poorly **Exceptionally well**

Reliability

Reliability is defined as how often the controller did something you didn't want or didn't expect.

How often did you find the arm moved in a different way than you wanted or expected?
Mark with an "x" on the line below.

Very frequently **Very infrequently**

Usability by Degrees of Freedom

Please rank the controllable actions of the desktop-mounted robotic arm (hand open, hand close, rotate palm up, rotate palm down, elbow flex up, elbow extend down, co-contraction if applicable) in order of which felt easiest to control with your muscle signals:

(easiest) 1. _____ 5._____

2. _____ 6._____

3. _____ 7._____

(most difficult) 4. _____

What about the most difficult degree of freedom did you find most challenging about controlling it?

Which of the pre-evaluation training exercises did you find most useful for improving your control over the robotic arm and in what way?

Participant # _____ Date: _____

If you have any additional comments, please write them on the back of this sheet.

Appendix D: Recruitment Flyer

Looking for research participants with normal arm function!

We are looking for research participants to learn to operate a robotic arm. This will involve up to 8 visits of a **maximum of 2–3 hours** to train to use the arm.

Your participation will help us advance research into advanced technology for artificial arms!

If you are interested in participating in this study, please contact:

blinc.lab.uofa@gmail.com or **call 780-492-4736**

Study Title: Evaluation of Advanced Control Strategies for Upper-Limb Prosthetic Devices
Primary Investigator: Dr. Jacqueline Hebert, Division of Physical Medicine and Rehabilitation 780-248-5767

University of Alberta Research Ethics Board 2 (REB2). Protocol: Pro00079472.
Version 3:February 6, 2018