# Extending Myoelectric Prosthesis Control with Shapable Automation: A First Assessment

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## ABSTRACT

For many users of myoelectric prostheses there is a set of functionality which remains out of reach with current technology. In this work, we provide a first assessment of an extension to classical myoelectric prostheses control approaches that introduces simple automation that is shapable, using EMG signals. The idea is not to replace classical techniques, but to introduce automation for tasks, like those which require the coordination of multiple degrees of freedom, for which automation is well-suited. A prototype system is developed in simulation and an exploratory user study is performed to provide a first assessment, that evaluates our proposed approach and provides guidance for future development. A comparison is made between different formulations for the shaping controls, as well as to a classical control paradigm. Results from the user study are promising: showing significant performance improvements when using the automated controllers, and also unanimous preference for the use of automated controllers on this task. Additionally, some questions about the optimal user interaction with the system are revealed. All of these results support the case for continued development of the proposed approach, including more extensive user studies.

## Categories and Subject Descriptors

J.3 [**Computer Applications**]: Life and Medical Sciences

## Keywords

myoelectric prosthesis control; automation; human-robot interaction

## 1. INTRODUCTION

Research into the myoelectric control of prostheses has been ongoing since the 1960's [21]. Significant and impressive advances have been made, from the hardware and electronics that enable onboard control, to signal processing techniques that decode the EMG signals. The most common control paradigms employed today are limited however to effectively control one degree-of-freedom (DoF) at a time, and lacking functionality is one reason for low adoption rates [3, 4, 15, 16].[1] For this reason, we hypothesize that the interface between users and their prostheses can be improved, both in capability and in user acceptance, by introducing a set of shapable automated controllers that can provide helpful motions and improved interactions with the device. In particular, tasks requiring the coordination of multiple degrees of freedom are well-suited to automation, but can be a challenge with individual-DoF control paradigms.

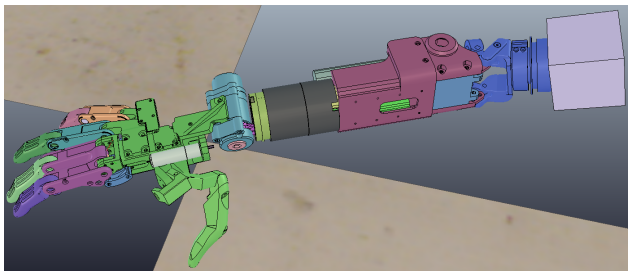

**Figure 1: Simulated model of the 5-DoF CBM prosthetic arm (Beta-1 prototype).**

In this work, we propose a framework to extend, rather than replace, traditional single-degree-of-freedom control. Our framework incorporates automated controllers, the behavior of which can be shaped online via myoelectric signals. The ability to shape the motion is critically important to the framework, because it allows the controllers to remain simple, and yet generalizable to the needs of a task (e.g. the stroke used with a hammer tends to increase once the nail is set), or to slight differences between tasks (e.g. the hand crank on a fishing rod is smaller than the circular motion you might use whisking pancake batter). The guiding vision is that of a toolbox of simple, shapable, automated motions that can handle a set of critical tasks not achievable with single-DoF control, to improve the user interactions with this important assistive technology. The shaping controls are the interface between the user and the machine, thus exploring different approaches for optimizing these control interactions is of significant interest in this work.

To demonstrate and evaluate the concept of introducing shapable automated controllers to the repertoire of controls

[1] Other reasons for low adoption rates include poor hardware durability, fatiguing interfaces, and user discomfort [4].


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available to an upper-limb prosthesis user, this work reports on an early-stage user study within a simulated environment using a model of an upper-limb prosthesis being developed at the Rehabilitation Institute of Chicago (RIC) and controlled by the EMG signals from human subjects (Figure 1). The task, turning a hand crank, was chosen because it requires a motion with hallmark characteristics suitable to automation (e.g. repetition and coordination of multiple DoF). The user study in this work is intended to investigate our hypothesis that performance of a traditionally difficult task can be improved with our framework, and to evaluate the effectiveness of different control interactions between the user and the machine. The information from this user study is intended to help prioritize and guide future development by highlighting the shaping control formulations with potential for high impact for prosthesis users. In addition to the performance aspect, the user study is intended to help gauge how users respond to controlling an automated motion within an alternative control space (i.e. controlling the amplitude and speed of a circular motion, instead of directly).

In Section 2 we present a brief overview of relevant research in to myoelectric prosthesis control and shared human-robot control, and literature assessing the needs of upper-limb prosthesis users. Section 3 introduces our framework and details of the implementation of our prototype system. In Section 4 we describe the methods used for the initial user study, followed by the results in Section 5. Finally, we discuss some insights from the study and areas for future work in Section 6 and conclude the work with Section 7.

## 2. BACKGROUND

While the use of automated controllers in myoelectric prostheses is a largely open area, it builds on a strong foundation of research and development that has occurred in pursuit of effective myoelectric control of upper-limb prostheses. What follows in this section is a brief overview of relevant research in myoelectric control of upper-limb prostheses, followed by a discussion of some of the important areas of related robotics research.

In early myoelectric prostheses, each degree-of-freedom was controlled by the contraction of a muscle pair, such as the bicep and triceps, where each muscle controls one half of the DoF, such as flexion or extension of the elbow. Switching control between the available DoFs was then accomplished by using a separate signal such as a co-contraction of the muscle pair or a hardware switch [21]. Using an antagonistic muscle pair configuration has the advantage of physiological intuition, but it is also limited in the number of control signals that it can generate.

With an estimated 1.6 million people in the United States alone living with the loss of a limb and an estimated 185,000 who undergo a limb amputation each year [28], the public health impact of advancing the technology of assistive prosthetics is major. A survey [3] of 1,575 prosthesis users in the United States in 1996 points to a want for better control mechanisms (including less visual attention) and the coordinated motion of two joints; characteristics also reflected in their top desired activities (e.g., turning a doorknob). A need for the proportional and simultaneous control of multiple DoF is noted repeatedly [3, 17, 18]. Limited dexterity and unsatisfactory control paradigms are often cited as reasons for the rejection of upper-limb myoelectric prostheses [4, 20]. Also noted is a current lack of non-fatiguing control interfaces for users of myoelectric hands [27], the control of which requires expending a large portion of their energy and concentration [25]. As a result, many electric prostheses often are used only aesthetically, not functionally, and a majority of prosthesis users still prefer body-powered mechanisms or simply using their other hand (for unilateral amputations) [3, 4, 15, 16].

Today, the most innovative techniques are looking at alternate ways to produce control signals; for example, the targeted muscle reinnervation (TMR) approach pioneered by Dr. Todd Kuiken [10, 11]. In the TMR technique, the residual nerves are surgically moved from the residual limb to another muscle (e.g. the pectoral muscle), with the benefit of allowing users to generate the control signals using the same nerve pathways that previously controlled their missing limb, and providing a larger site for electrode placement.

Advances in discriminating control commands from myoelectric signals include most notably pattern matching techniques that classify an array of EMG nodes [20]. The most advanced techniques are able to discern 10-12 motion classes [20, 24], that typically each map to one half of a DoF (one class per motion direction). The most widely used techniques [2, 5, 13, 20, 23, 24] still control each DoF individually and sequentially—e.g., to move the elbow, then the wrist, then close the hand—and asking a user to simultaneously generate signals for more than one class at a time is generally impractical due to high cognitive load [11, 16].

Recent academic work within the field of simultaneous control thus has emphasized alternative mapping paradigms. For example, pattern matching classes that encode multi-DoF motions [22] or force functions for each joint [9]; or direct control within a reduced dimensionality space [14]. Much of this work is motivated by the idea of muscle synergies, that activate in coordination rather than individually.

A small number of works have introduced some element of automation. The lower-level control of hand gripping was automated in the MANUS Hand [19], and different levels of shared human-machine control were evaluated with the CyberHand [6]. Automation was found to make the task less difficult for users, and require less attention.

The partial automation of electric prostheses has much in common with the domain of shared human-robot control. Here the goal is often to find a sweet spot—on the continuum spanning from fully manual (e.g., teleoperation) to fully automated control—that makes the system more capable than at either extreme [7, 8, 12, 26]. Typically the cognitive load on the machine is greatly reduced in shared control paradigms, and the automation consequently is that much more robust. In this work, the prosthesis user and the prosthetic arm operate in concert within a shared human-machine control paradigm with the goal of both enhanced functionality and user acceptance.

## 3. PROPOSED FRAMEWORK

In order to implement our prosthetic limb control system within a simulation environment, a parameterized automated controller for the prosthesis model and the EMG control system need to be developed for testing the shaping controls. What follows is a discussion of the formulation of each of the subcomponents of our prototype system.

A few notes about convention. When referencing time series elements, $\tau$ represents the wall-clock time, so $\Delta\tau$ is the temporal resolution of the simulator (in our case 0.050

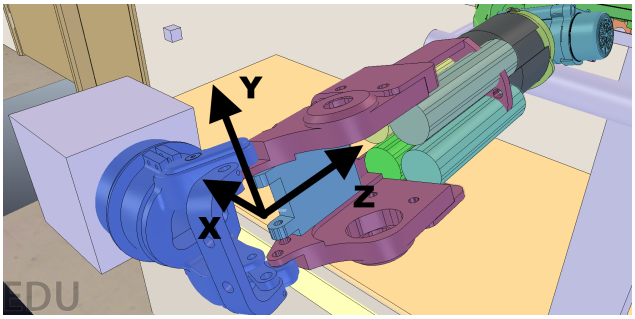


**Figure 2: Coordinate frame used for calculating the circular motion of the end effector.**

seconds), while $t$ represents the time index. Thus, the difference between $t$ and $t+1$ is $\Delta\tau$. Additionally, bold font is used to represent vectors.

## 3.1 Automated Controller with Shaping

The automated controller implemented in this work creates a periodic circular motion at the end-effector using a general sinusoidal oscillator, in which the amplitude, $\alpha$, and angular frequency, $\omega$, are modulated by shaping controls, $\boldsymbol{\theta}$, and the phase, $\phi$, is solved for in order to provide smooth transitions between changes in $\omega$.

By choosing an appropriate reference frame relative to the end of the humerus side of the elbow joint at the point of joint rotation (Figure 2), the position $\boldsymbol{p}$ of the target end-effector pose can be made circular regardless of the absolute position of the prosthetic arm in space. An oscillator then updates the $x$ and $y$ components of target end-effector position according to Equations (1) and (2) and the $z$ component is held constant as the length of the forearm segment, $l$, of the prosthetic arm (Equation (3)).

$$p_x = \theta_\alpha \; cos(\theta_\omega \tau + \phi^t) \tag{1}$$

$$p_y = \theta_\alpha \; sin(\theta_\omega \tau + \phi^t) \tag{2}$$

$$p_z = l \tag{3}$$

In general, a transition occurring due to changes in the amplitude shaping control $\theta_\alpha \in \boldsymbol{\theta}$ is smooth, but changes in the angular frequency shaping control $\theta_\omega \in \boldsymbol{\theta}$ can cause rapid jerks forward or backward around the circle, behaving as a sort of time warp, since the phase is being changed. To smooth out these transitions, a new $\phi^t$ can be calculated for each new value of $\theta_\omega$ using the equality described in equation (4) to ensure that the end-effector continues smoothly around the circle despite the change in $\theta_\omega$.

$$\theta_\omega^t \tau + \phi^t = \theta_\omega^{t-1} \tau + \phi^{t-1} \tag{4}$$

In order to convert this end effector pose control to velocity commands in the joint space at time $t$, the target position of the end-effector position is projected forward to time $t+1$. The inverse kinematic (IK) problem for the projected end-effector position $\boldsymbol{p}^{t+1}$ is then solved using a damped least squares IK solver. Finally, the joint velocity commands $\dot{\boldsymbol{\varphi}}^t$ are calculated from the current and projected joint positions $\boldsymbol{\varphi}^t$ and $\boldsymbol{\varphi}^{t+1}$ according to Equation (5).

$$\dot{\boldsymbol{\varphi}}^t = \frac{\boldsymbol{\varphi}^{t+1} - \boldsymbol{\varphi}^t}{\Delta\tau} \tag{5}$$

## 3.2 The Shaping Controls

With multiple ways to formulate shaping commands for an automated motion, we want to determine which formulation can facilitate more effective interactions between user and machine. To begin to answer this question, this system implements two different formulations for controlling the shaping controls, one discrete and one continuous. In the discrete formulation, the shaping control is adjusted by discrete constant amounts. With the continuous formulation, the proportional value of the muscle activation is mapped to the range of values the shaping control can take on.

Two opposing muscle groups are used in the EMG control system, the right biceps and triceps. One electrode is placed on the skin over each of the muscle bellies. Each channel of the raw signal $\boldsymbol{s}$ is sampled at a frequency of $1000Hz$. The root mean square (RMS) feature, $m(s_i)$, $s_i \in \boldsymbol{s}$, of each channel in the raw signal is calculated according to Equation (6), where the window size $N$ is set to 150.

$$m(s_i) = \sqrt{\frac{1}{N}(s_{i,1}^2 + s_{i,2}^2 + ... + s_{i,N}^2)} \tag{6}$$

Before the EMG control goes online, there is a calibration step in which the subject is asked to relax for some time, and a resting baseline $\boldsymbol{\beta}$ is estimated. $\boldsymbol{\beta}$ is a vector containing the RMS feature calculated for each channel of the signal recorded over that time period, and this resting baseline is subtracted from incoming EMG signals. The RMS feature, less the baseline, is then used to determine if the muscle activation is over the channel threshold $\lambda_i$, represented by the binary variable $\gamma_i$ according to Equation (7).

$$\gamma_i(m_i, \beta_i, \lambda_i) = \begin{cases} 1 & : m_i - \beta_i \geq \lambda_i \\ 0 & : m_i - \beta_i < \lambda_i \end{cases} \tag{7}$$

where $i = \{biceps, triceps\}$

The way $\boldsymbol{\gamma}$ is used is dependent on the formulation (discrete or continuous) of the shaping control, described below.

### 3.2.1 Discrete Shaping Control Formulation

In the discrete control formulation, the currently selected shaping control is updated by a set increment $\Delta\theta_i$ according to the rule defined by equation (8).

$$\theta_i^t = \begin{cases} \theta_i^{t-1} + \Delta\theta_i & : \gamma_{biceps} = 1 \wedge \gamma_{triceps} = 0 \\ \theta_i^{t-1} - \Delta\theta_i & : \gamma_{biceps} = 0 \wedge \gamma_{triceps} = 1 \\ \theta_i^{t-1} & : otherwise \end{cases} \tag{8}$$

where $i = \{\alpha, \omega\}$

### 3.2.2 Continuous Shaping Control Formulation

In the continuous control formulation only one muscle group is considered and the value of the shaping control is determined by mapping the proportional value of the muscle contraction to the range of shaping control values, as in Equation (9). Accordingly, there is an additional calibration step to set the full range of muscle activity before the control goes online. In this calibration step the user is asked to flex the controlling muscle (biceps) with maximal effort, $m_{max}$.

$$\theta^t = \theta_{min} + (\theta_{max} - \theta_{min}) \frac{m^t}{m_{max} - \lambda} \tag{9}$$

The prosthesis joint limits and the controller determine the possible range $[\theta_{min}, \theta_{max}]$ of shaping control values.

## 3.3 Direct Control

We also implement a simplified version of classical single-DoF control (now on referred to as *direct control*), to act as a reference for the performance comparison. The direct control operational mode is formulated in a very similar way to the discrete control of the shaping controls presented in equation (8), with the major exception being that the joint angles are updated directly as opposed to the shaping control values. The two joints involved in the particular task we have implemented are the elbow joint and the wrist extension and flexion joint. With this in mind, a long co-contraction of muscles would initiate a grasp, a short co-contraction would switch which joint was selected for control, and then the activation of biceps and triceps would map to flexion and extension of the active joint respectively.

## 3.4 Task Execution

In our implementation of a crank turning task, a long (>1.5 second) co-contraction of the biceps and triceps triggers the start of the automated behavior, which begins by grasping the crank handle and starting the rotation. The user then selects the amplitude shaping control $\theta_\alpha$ with a short (0.75 to 1.5 seconds) co-contraction of the biceps and triceps; throughout this operating mode, short co-contractions will flip which shaping control ($\theta_\alpha$ or $\theta_\omega$) is selected. The amplitude can then be tuned: where a biceps contraction increases (and a triceps contraction decreases) the amplitude by modulating $\theta_\alpha$. The angular velocity can also be tuned by modulating $\theta_\omega$ in the same manner.

Unlike amplitude, the angular velocity can take on both positive and negative values. The shaping control $\theta_\omega$ thus is formulated to set both rotational speed and direction, smoothly. In particular, a biceps contraction increases the value of $\theta_\omega$, and a triceps contraction decreases its value. Thus, when $\theta_\omega$ is positive (clockwise rotational direction) a triceps contraction slows down the rotation; however, once $\theta_\omega$ is sufficiently decreased to be negative, the increasingly negative numbers of a triceps contraction will speed up the (counter-clockwise) rotation.

The task we evaluate with our user study is to turn the hand crank 10 revolutions in one direction, followed by 10 revolutions in the opposite direction. This task embodies the type of repetitive, multi-degree of freedom task to which automation is well suited.

# 4. USER STUDY METHODS

Here we first describe the user demographics, followed by the system implementation and study metrics. For practical purposes relating to fatigue and frustration, the users were given a time limit of eight minutes to complete the task. Each user was given up to 30 minutes to familiarize themselves with the task and the controls. One important note, during the trial using the continuous shaping control formulation, it is the amplitude that is set proportionally; the angular speed is set via the discrete shaping control formulation. The order in which the control formulations were used was randomized to minimize ordering effects.

## 4.1 User Demographics

This exploratory user study was performed under IRB protocol STU00084001. Participants consisted of five able-bodied users, three male and two female, between 24-32 years old. Each user was instructed to complete the task using all three control formulations (direct, discrete, and continuous). Two of the five users had prior experience with EMG recording. The results and insights gleaned from this initial assessment are meant to guide further investigation with additional subjects and implemented tasks.

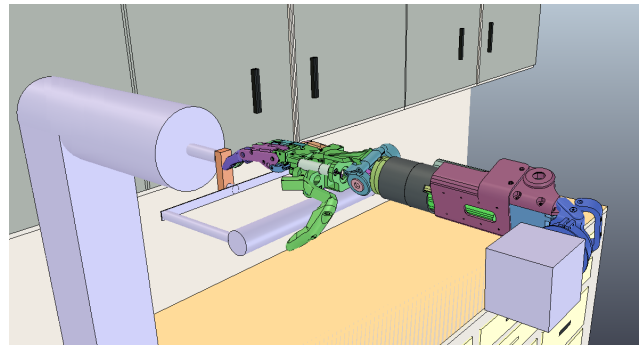

**Figure 3: The view of the arm model and hand crank in the simulator for the task of turning the crank 10 times in each direction.**

## 4.2 Virtual Environment

The simulation environment utilized the Virtual Robot Experimentation Platform (V-REP): a 3D physics-based simulation environment, using the ODE and Bullet dynamics engines [1]. We have built a model for an upper limb prosthesis, the 5-DoF CBM prosthetic arm (Beta-1 prototype) from the Center of Bionic Medicine at RIC (Figure 1). The position and orientation of the prosthetic limb was anchored in space, such that the task was achievable given appropriate EMG inputs.[2] The simulator was projected on to a large screen to give a more familiar sense of scale while performing the task. See Figure 4 to see the setup.

A Measurement Computing USB-1408FS DAQ converts the analog signal from an Aurion (now Cometa Systems) ZeroWire EMG system into a digital signal, which is then provided to a PC via USB. Matlab and the Data Acquisition Toolkit interfaces with the DAQ, where the EMG signals are processed and then the commands are passed to V-REP.

## 4.3 Study Metrics

A number of objective metrics are evaluated. *Task Completion* is a boolean variable indicating whether or not the user was able to complete the task within the eight minute time window. The eight minute task time limit was set to avoid fatigue, which could affect subsequent trials, and limit frustration. *Execution Time* is simply the number of seconds spend on the task, up to 480. *Number of Commands Issued* is a direct count of the number of 150ms time windows in which the user's muscle activity was over the threshold which results in a command being issued. The reason the number of commands metric is important is it is an indirect measure of muscular effort put forth by the user, since increased muscle activity is required to issue a command.

[2]Future work will consider mapping the position and orientation of the user's arm in the real world to the simulated environment to provide a more realistic evaluation. This could be accomplished using tracking from a sensor such as the Microsoft Kinect. However, in this work we anchored the arm to focus on the EMG control alone.

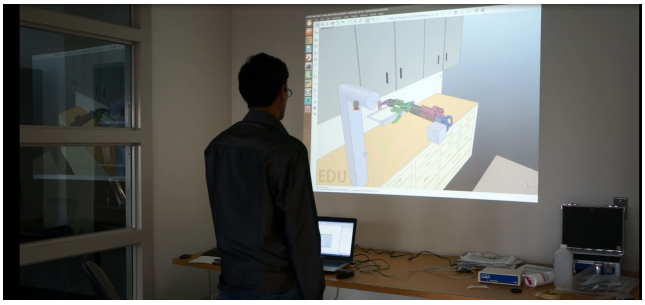

**Figure 4: A user completing a task in the virtual environment, by using EMG to shape the motion of the automated prosthesis controller.**

Subjective data was gathered via a brief questionnaire (IRB STU00084001) given at the conclusion of the study, to determine user preferences. Subjects were asked if they preferred the direct control or automated control formulation. If automated control was preferred, then they were asked which shaping control formulation they preferred, discrete or continuous. To explore user opinions about their preferred system, they were given six statements and asked to rate each one on a Likert scale according to their agreement with the statement. Where a value of one indicates strong disagreement, a value of four is neutral, and a value of seven indicates strong agreement:

1. **Capability:** The system was able to complete the tasks of the experiment.

2. **Capability:** I think the system would be able to complete other tasks.

3. **Utility:** The system was useful for completing the tasks of the experiment.

4. **Utility:** I think the system would be useful for completing other tasks.

5. **Ease of Use:** The system was easy to use.

6. **Intuition:** The system was easy to learn how to use.

The next portion of the questionnaire consisted of two open-ended questions eliciting suggestions about alternative methods for shaping an automated motion and alternative automated motions that would be useful in their daily tasks. Lastly, there was a question regarding the ability to design their own automated motions. This was a multiple choice question will several possible options, an open-ended 'other' answer, and an answer for 'no interest'.

# 5. RESULTS

In order to investigate the potential value of the proposed approach, we look at objective performance data, and the subjective perceptions of the users. In this section we present the objective data first to examine the support for the proposed approach, and then the subjective data gathered from our questionnaire.

**Table 1: Execution Time (in seconds)**
*Successful executions in bold.*

| Subject | Direct | Discrete | Continuous |
|---|---|---|---|
| 1 | 480 | **174.9** | **204.5** |
| 2 | 480 | **155.9** | **128.7** |
| 3 | 480 | **125.2** | **141.4** |
| 4 | 480 | **161.4** | **216** |
| 5 | 480 | **107.0** | **129.4** |
| Mean ± StDev. | 480 ± 0 | **144.9 ± 25** | **164 ± 38** |

## 5.1 Objective Performance Metrics

The objective metrics both highlighted the potential of our approach for improved task performance and left some open questions regarding the best shaping formulation for improved user interactions.

### 5.1.1 Task Completion

For task completion, eight minutes was not enough time for any of the subjects to complete the task using the direct control method. Of the five subjects, two were not able to achieve more than one revolution of the hand crank using direct control. The other two subjects were able to nearly complete 10 revolutions of the crank in a single direction before time ran out, and the remaining subject completed two revolutions. By contrast, all five subjects were able to complete the task with the automated control paradigm using either shaping control formulation.

The failures of the direct control stemmed from the fact that, to perform this task, a significant amount of switching had to occur between the two controlled joints. Sometimes there would be unsuccessful switches between the joints due to inadequate muscle activation, causing the actual execution of the movement to get out of sync with the users expectation of what movement their command would elicit.

### 5.1.2 Execution Time

The time to complete the task is really the most telling metric when it comes to judging the performance of the automated control solutions versus the direct control. While 480 seconds was not enough to complete the tasks using the direct control, both the discrete and continuous shaping control formulations of the automated control required less than half the allotted time to fully complete the tasks (Table 1). While the difference between the automated control methods and the direct control is quite evident, the difference between the discrete and continuous shaping control formulations is less clear. Although the average time with the discrete formulation was lower than the continuous formulation by 18 seconds, this difference is not statistically significant ($p < 0.43$, two-tailed, paired-sample t-test).

### 5.1.3 Number of Commands Issued

Another metric that provides insight into the performance of these control paradigms is the number of commands issued by the user via EMG. This metric can be useful as an indicator of user effort. In Table 2, the automated controllers again far outperform direct control, requiring fewer commands; moreover, even with issuing more commands, the direct control paradigm never allowed for the successful completion of the task. This result holds even when looking at the average number of commands per second.

**Table 2: Number of Commands Issued**
*Successful executions in bold.*
*Average number of commands per second in parentheses.*

| Subject | Direct | Discrete | Continuous |
|---|---|---|---|
| 1 | 343(0.72) | **86**(0.49) | **56**(0.27) |
| 2 | 320(0.67) | **63**(0.40) | **45**(0.35) |
| 3 | 161(0.34) | **74**(0.59) | **50**(0.35) |
| 4 | 196(0.41) | **58**(0.36) | **42**(0.19) |
| 5 | 301(0.63) | **53**(0.50) | **31**(0.24) |
| Mean ± StDev. | 255 ± 72 | **66.8 ± 11.9** | **44.8 ± 8.4** |

Interestingly, when comparing the discrete and continuous shaping control formulations, the continuous formulation requires significantly fewer commands ($p < 0.016$). This makes sense when one considers that the amplitude can be set proportionally with a single command using the continuous formulation. As it turns out, there was enough compliance in the task (in the grip of the hand and compliance in the crank handle), that several of the subjects were able to set the amplitude within one or two tries using the continuous formulation. Future work will examine setting the rotational speed and direction using the continuous formulation as well, which could magnify this difference further by reducing the number of commands issued using the continuous formulation.

## 5.2 Subjective Performance Metrics

To help complete the picture of how well these paradigms perform, a questionnaire was administered following completion of the three task executions. The users were asked two multiple choice questions regarding preference of control paradigms. Additionally, they were asked to give a rating on a Likert scale regarding agreement with statements about ease of use, intuition, capability, and utility. Finally, there were a number of open-ended questions asking for feedback about additional motions that might be useful, additional formulations for shaping controls, and being able to define new motions and their shaping controls.

### *5.2.1 User Preference*

When asked whether users preferred direct control versus automated control in completing this task, the users unanimously chose automated control. This was not surprising given the negative reactions of the users to direct control during the trials. Of more interest was the response to shaping control formulation preference. In this case, the users were again unanimous in that they preferred the discrete formulation to the continuous formulation. This is despite the fact that the continuous formulation required less muscular effort, as noted in Section 5.1.3.

### *5.2.2 User Opinion*

The users were asked to rate several statements (detailed in Section 4.3) on a Likert scale of one to seven. Figure 5 highlights that users had the highest level of agreement with the statements about the capability of their preferred system (statements 1 and 2), believing that the system was capable of completing the task of the study, as well as other potential tasks not included in the study. With respect to the utility of the system (statements 3 and 4), these statements required the user to go beyond just believing that the system could

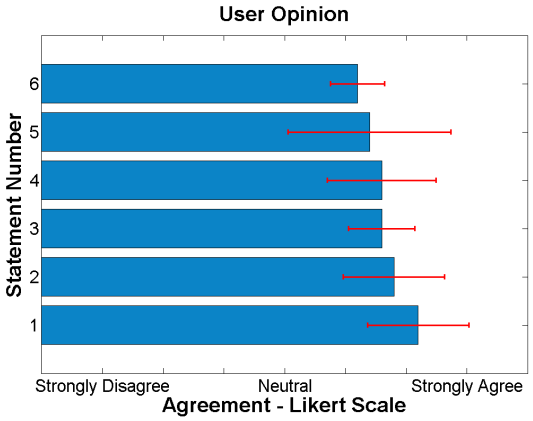


**Figure 5: Mean Likert scale values of the user responses to the statements detailed in Section 4.3. Error bars represent one standard deviation.**

accomplish a task to believing that accomplishing that task would actually be of utility to them. While the agreement weakened slightly, it was still quite positive. Statement 5 related to how easy the preferred system was to use, and in this statement the users were more conflicted, with two users being neutral, one strongly agreeing, and the remaining two falling in between. The result was weak agreement. The sixth and final statement was about how easy it was to learn how to use the system. Once again, there was weak agreement that the system was easy to learn. Seeing as these were users with limited experience and practice with both EMG recordings and the system in general, it makes sense that the lowest scores are related to the ease of use.

### *5.2.3 User Feedback*

The questionnaire solicited feedback from the users regarding ideas for additional automated motions that would be useful, alternative methods for shaping the automation, and preferred interfaces for defining their own new automated controllers. These questions proved to be challenging and the responses were minimal. The first question asked "Can you imagine other ways to shape an automated motion?" and only one subject had a response, which was to use muscle groups that were easier to differentiate. The second question asked "Are there other automated motions that would be useful for performing your daily tasks?" One user suggested grasping a phone and bringing it to her head, another user suggested opening the fridge or a door. Another user captured the more general thrust and suggested just being able to grasp and pick something up. In these cases, the suggestions were more task focused, which might be in interesting principle to incorporate in to the framework. Likely, these questions were challenge because each user had full use of their arms and hands, and as such had trouble envisioning the difficulties faced by persons with amputations. We expect these particular questions to be more informative in future studies with individuals with amputations and the clinicians who work with them.

# 6. DISCUSSION AND FUTURE WORK

As mentioned, the purpose of this study was to provide a first assessment of our proposed system, that will be used to

guide future research. The most basic question to assess was whether or not the users would be able to perform the tasks well using our semi-automated control framework. We can say unambiguously that for this task, the user performed much better when using semi-automatic control. This is important support for our proposed framework, which motivates further development and evaluation of user capability. It would be interesting in future studies to go beyond comparisons to other myoelectric control systems, and compare with the capabilities of an expert body-powered prosthesis user as well. In so doing, the advantages of incorporating semi-autonomous behaviors would be tested against the most popular tool for persons with amputations.

Another important question that this user study intended to address related to the user interfacing with the machine; namely, which formulation for shaping controls would be the best. In this, the user study did not differentiate one over the other in a meaningful way. On the one hand, the users were slightly faster with the discrete shaping control formulation. On the other hand, they used less muscular effort with the continuous shaping control formulation. It is not immediately clear the reason for these results, but one possibility is related to the fact that all of these users were able-bodied, novice users of EMG systems. One of the principle strengths of the discrete shaping control formulation is that it allows for a more forgiving experience, because if an erroneous command is provided, it may only change the motion a small amount which can quickly be corrected. With continuous shaping controls, it is very easy to accidentally change the value of the shaping control a large amount, if say a mode change via co-contraction doesn't occur as expected. In a system in which the only feedback is visual confirmation of your command being executed, the higher cost of mistakes present in the continuous shaping control formulation can be daunting for a novice user. However, if a certain level of mastery was achieved using the continuous shaping controls, it is plain to see that significantly fewer commands would be needed, meaning faster execution times and reduced effort on the part of the user.

What this means going forward is that we can not yet throw either formulation out, but an expanded study is warranted to see if the promise of the continuous shaping control formulation pans out within a more experienced target population. It will also be important to see if a general formulation trend is seen across multiple automated controllers and shaping controls. It is possible that users never achieve the level of proficiency with the continuous shaping control formulation envisioned here, due to the noisy signals generated by EMG, and that the formulation thus never achieves a high level of acceptance. Additionally, non-visual feedback is another avenue for study that could tip the scales towards one shaping control formulation or another.

From a more anecdotal perspective, it was interesting to see the users during the initial practice session trying to learn how to control the individual muscles precisely enough to engage the system reliably. Once muscle control was sufficiently "mastered", they would then spend time trying to understand the control methods themselves. During this practice session, users would often verbally express confusion and doubt about the ability to control the motion, but would slowly improve their control. Finally, after having some experience and frustration with the direct control, the response was overwhelmingly positive when then switching back to the automated solutions. The side-by-side comparison between the automated and non-automated solutions we believe can explain the significantly positive views expressed by the users. It will be interesting to see if more experienced users with amputations feel as positively about the system.

With the encouraging results from this user study, there are several avenues for additional work. The first area of work is to improve the realism of the simulation by allowing the user to move the prosthesis around as if it were attached to their upper arm. Work in this area is ongoing. Another area is to identify additional tasks that are of interest to persons with amputations and develop automated solutions within our framework to ensure that the results of this study apply broadly. Finally, studies with more subjects, including persons with an amputation, is the necessary next step to fully asses the value of our proposed framework.

# 7. CONCLUSIONS

This work has presented a first assessment of a framework for adding automated motion control to myoelectric prostheses, in order to augment classical control methods which only actuate a single degree of freedom at a time. Our proposed framework parameterizes the automated controller so that users may shape the automated motion using the existing EMG control apparatus, by modulating this parameterization. In order to investigate the question of user interfacing with the system, two separate formulations were considered, discrete and continuous, each of which may provide different benefits. Within this work, compelling support for the value of this framework is provided through an early-stage user study which indicates greatly improved performance in a repetitive task requiring the coordinated actuation of multiple degrees of freedom. The users unanimously preferred the automated solution to the classical single-degree-of-freedom control. Additionally, while the novice EMG users in this study overwhelmingly preferred the discrete formulation of the shaping controls, the continuous shaping control did decrease the muscular effort required to set the value, prompting the question of whether an expert user might prefer the continuous shaping control formulation. On going studies will address this question.

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