Evaluation of Myoelectric Control Learning Using Multi-Session Game-Based Training

Aaron Tabor, *Student Member, IEEE*, Scott Bateman, and Erik Scheme, *Senior Member, IEEE*

***Abstract*— While training is critical for ensuring initial success as well as continued adoption of a myoelectric powered prosthesis, relatively little is known about the amount of training that is necessary. In previous studies, participants have completed only a small number of sessions, leaving doubt about whether the findings necessarily generalize to a longer-term clinical training program. Furthermore, a heavy emphasis has been placed on a functional prosthesis use when assessing the effectiveness of myoelectric training. Although well-motivated, this all-inclusive approach may obscure more subtle improvements made in underlying muscle control that could lead to tangible benefits. In this paper, a deeper exploration of the effects of myoelectric training was performed by following the progress of 30 participants as they completed a series of ten 30-min training sessions over multiple days. The progress was assessed using a newly developed set of metrics that was specifically designed to quantify the aspects of muscle control that are foundational to the strong myoelectric prosthesis use. It was determined that, while myoelectric training can lead to improvements in muscle control, these improvements may take longer than previously considered, even occurring after improvements in the training game itself. These results suggest the need to reconsider how and when transfer from training activities is assessed.**

***Index Terms*— Myoelectric control, myoelectric training, therapeutic games, clinical outcome measures.**

I. Introduction

LEARNING to control a prosthesis by any means is a complex and difficult task. Myoelectric control of a prosthesis, which uses the electrical signals generated during the contraction of residual musculature [21], is arguably even more complex as it requires the user to not only adapt to a new device, but to also learn how to properly contract those muscles.

Training is therefore considered to be an essential step in the rehabilitation process, possibly leading to more effective and prolonged use of a prosthesis [26]. Access to early myoelectric training is also thought to aid in preventing the development and habituation of one-handedness, a mindset that can deter patients from myoelectric control and lead them to abandon their prosthesis [3]. Despite the clear benefits of training, patients often do not get enough training in clinical practice. Recent studies have found that as many as 75% of prosthesis users ultimately abandon their device [2], with 30% explicitly stating that they did not get the therapeutic attention they needed or desired [15]. This suggests that high abandonment rates are at least partially linked to insufficient training [31].

Even though myoelectric training is a popular area of research, little is known about how myoelectric control develops over time. Whether by intentional design or imposed through practical restrictions (e.g., availability of amputee participants), many studies have considered only a very short series of training sessions when exploring the effects of training, suggesting that their findings may only be applicable to the very early stages of training. In many previous experiments, participants have completed only four or fewer short training sessions [4], [5], [8], [9], [22], [33], [35], [36], [38], so new information about the effects of training can still be gained by exploring myoelectric training over a longer series of sessions.

Furthermore, a heavy emphasis has been placed on functional prosthesis use when evaluating the improvement achieved through myoelectric training. Previous research has focused solely on improvements in specific aspects of prosthetic control when assessing training success, such as matching hand-aperture to a target object size [8], [9] or overall completion time of a prosthetic grabbing task [35], [36]. Evaluating early training progress in this way may not provide a sufficiently resolved measure of improvement because prosthetic control is a complex, multi-skilled task. For example, even though clinical experts focus specifically on developing muscle control in early training [27], [30], improvement in these skills may not necessarily result in immediate improvement in prosthetic control and may therefore be overlooked when training progress is simply judged on functional ability. This is important because these subtle improvements could

Manuscript received October 13, 2017; revised February 20, 2018 and May 25, 2018; accepted June 28, 2018. Date of publication July 12, 2018; date of current version September 6, 2018. This work was supported in part by the NSERC Discovery under Grant 2014-04920 and in part by the New Brunswick Innovation Foundation. *(Corresponding author: Erik Scheme.)*

A. Tabor is with the Human Computer Interaction Laboratory, Faculty of Computer Science, and the Institute of Biomedical Engineering, University of New Brunswick, Fredericton, NB E3B 5A3, Canada.

S. Bateman is with the Human Computer Interaction Laboratory, Faculty of Computer Science, University of New Brunswick, Fredericton, NB E3B 5A3, Canada.

E. Scheme is with the Department of Electrical and Computer Engineering, and the Institute of Biomedical Engineering, University of New Brunswick, Fredericton, NB E3B 5A3, Canada (e-mail: escheme@unb.ca).

Digital Object Identifier 10.1109/TNSRE.2018.2855561

accumulate over time and may ultimately lead to better control and functional improvements. However, there is currently very little work that has investigated or quantified improvements in muscle control that may result before improvements in functional control.

In this study, a deeper exploration of how two-site proportional myoelectric control develops over time was conducted to better understand the longer-term effects of training. Participants were followed as they completed a series of ten 30-minute training sessions – a substantially longer series than has been completed in many previous studies. Maintaining motivation throughout a longer series of training sessions can be challenging [33], so a previously developed training game that was specifically designed to promote a fun and successful training experience was employed [31]. Improvement throughout these training sessions was assessed using a newly developed set of metrics that were created to quantify control signal quality and other characteristics considered to be important for proficient muscle control [30] (introduced in detail below). We propose that these metrics will more accurately reflect the type of improvement that clinical experts and therapists look for in early myoelectric training.

Through this work, it was determined that myoelectric training does indeed lead to improvements in muscle control, but – as is the case when learning many other complex motor tasks [18] – this improvement occurs more gradually than was anticipated in previous research. In the present study, improvement in muscle control occurred well after demonstrated improvements in the training game. These results suggest the need to reconsider how and when transfer from training activities is assessed.

In this paper, we introduce the newly developed metrics for assessing muscle control, present the results of a 300-session user study, and discuss the implications that these findings have for myoelectric training in both research and clinical practice.

II. Background

A. Myoelectric Control

Myoelectric control is an approach used to operate a powered prosthesis that continuously monitors the user's muscle contractions, using the signals acquired as input to control a terminal device [21]. Two-site proportional control, a specific implementation of myoelectric control, is commonly used by trans-radial amputees and operates using wrist flexor and extensor muscle contractions to control a prosthesis (e.g., hand open/close, wrist rotation) [11]. More sophisticated pattern-recognition based myoelectric control schemes exist that arguably provide superior dexterity and a more natural mapping of input to control [10], but have yet to gain widespread clinical adoption. Two-site proportional control remains the most popular choice for upper-limb amputees and was therefore of particular interest in this study because of the potential for near-term clinical impact.

B. Myoelectric Training

When learning to use a myoelectric prosthesis, access to early training is critical [3]. The literature suggests that patients should begin training no later than 30 days following an amputation surgery to maximize chances for success [14]. The fitting and fabrication of the patient's prosthesis, however, is often delayed beyond this 30-day period, so virtual training tools are sometimes used in early training. Tools such as the Ottobock PAULA software suite [20] can be used before a patient receives their prosthesis, providing a signal visualizer and virtual prosthesis simulator, which can help patients familiarize and build strength in their residual musculature [3].

While it is known that tools like the Ottobock PAULA suite [4] and other forms of training feedback [6], [29] can be very helpful for new prosthesis users first learning to use their device, previous studies exploring this learning have been completed over a very small number of training sessions. Previous studies have consisted of 4 [8], [9], 3 [4], [33], 2 [35], [36], and even 1 [5,22,38] training session(s), ranging from 3-80 minutes total training time. Since many other complex motor-control skills have been shown to develop gradually over time [7], [16], [18], [32], findings from these short studies may only apply to the very early stages of training, meaning that the longer-term effects of myoelectric training are still unclear.

In some scenarios, the small number of training sessions completed in these studies is understandable and unavoidable due to practical restrictions, such as the limited availability of amputee participants. However, even when participants are readily available, the monotonous and repetitive training tools used in many clinics make it difficult for patients and research subjects to stay engaged and motivated throughout training [31], [33]. Games have been proposed as a possible solution to this training problem [6], [8], [9], [22], which is why a game was selected specifically as the main training tool used in this study (introduced in detail below).

C. Assessing Myoelectric Performance

Tools for assessing levels of myoelectric skill and performance are used to evaluate and compare the effectiveness of different types of myoelectric training. Many of these assessment tools focus specifically on real-world, functional use of a prosthesis. The Southampton Hand Assessment Procedure (SHAP) [25] is one such tool intended to assess real-world hand function and consists of a series of timed tasks such as grabbing and moving common objects. Similarly, the Target Achievement Control (TAC) test [27] focuses on pseudo-functional prosthesis use and consists of matching a series of target hand poses with a virtual prosthesis.

Alternatively, Fitts-style targeting tasks have also been used in research [23], [36], and focus on speed and accuracy of myoelectric control in general. One previous study [22] conducted a preliminary examination of how training could lead to improvements in myoelectric skill by investigating aspects of muscle control such as levels of isolation between muscle sites and overall endurance. However, participants in this previous study completed only a single training session.

The focus of our work was to explore the improvements in these foundational aspects of muscle control in more detail, specifically examining if and how skills are

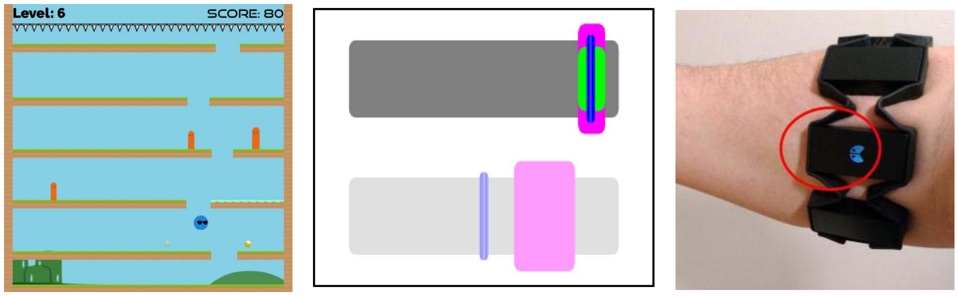

Fig. 1. Tools used in this study. a) The Falling of Momo, a myoelectric muscle training game b) MyoFitts, a myoelectric Fitts-style assessment tool c) Myo Armband, a consumer grade myoelectric input device (oriented according to manufacturer's suggested best-practices on the participant's right forearm – USB charging port facing distally, logo along inner forearm).

developed throughout a longer series of training sessions. In this work, a set of metrics was developed to quantify these skills [30], then used to track progress and improvement in muscle control over a series of training sessions (metrics are described in detail below). These metrics were used to demonstrate that muscle control develops more gradually and continually throughout training than has previously been considered.

III. Methods

A. Participants

Thirty healthy, able-bodied participants (68% identified as male, 32% female – mean age: 26.8 +/− 8.3) were recruited to participate in this study, as approved by the University of New Brunswick's Research Ethics Board (REB #2017-047).

Twenty-nine participants completed a full series of 10 training sessions, while one participant completed 8 sessions before withdrawing due to unrelated reasons and was excluded from further analysis. All participants confirmed that they had no previous experience with myoelectric control and completed all training activities using their dominant forearm (self-reported, confirmed with Edinburgh-handedness index [19]).

Training sessions were scheduled at the availability of participants, with the only restrictions being that a participant must complete no more than 2 sessions per day (separated by at least 6 hours), and no fewer than 2 sessions per week.

B. Apparatus

Two myoelectric-controlled training tools were used in this study: *The Falling of Momo* (*Momo*) and *MyoFitts*. Both tools were controlled using the Myo armband (Fig. 1-c), a commercially available myoelectric input device [17]. The armband, which performs onboard filtering of common artifacts such as powerline and heartbeat interference, samples and streams EMG at 200Hz. This signal was smoothed by computing the mean absolute value (MAV) of 150ms sliding windows (5ms increments). Both tools make use of velocity-based proportional control (i.e., harder contractions result in faster movements) and even though the armband provides eight EMG channels, only two were used during training to simulate a dual-site control policy (see below for details on sensor selection and calibration). Co-contraction impulses were triggered whenever both signals exceeded 80% of the calibrated proportional input range.

Momo (Fig. 1-a – github.com/hcilab/Momo) is an open-source myoelectric muscle training game that was designed specifically to promote fun and success while helping patients train and build muscle strength [31]. Players move Momo (round blue character) left and right with flexion and extension forearm contractions, respectively (mapping reversed when controlling the game using left forearm). Momo also jumps when a co-contraction impulse is performed. The goal of the game is to survive for as long as possible by falling through gaps in the rising platforms to avoid the spikes along the top of the screen; a round of play is concluded when Momo gets squished. As the game proceeds, platforms rise more quickly creating a fun and challenging training environment (see [31] for a more complete description of Momo's game mechanics and how they align with training goals)

MyoFitts (Fig. 1-b – github.com/hcilab/MyoFitts) is a Fitts-style assessment tool for evaluating an individual's abilities with myoelectric control. The assessment consists of a series of trials, with each trial consisting of 2 sequential targeting tasks (top and bottom bar visible in Fig 1-b). This design was intended to simulate the coordinated wrist-rotation and hand-aperture adjustments performed in dual-site proportional control. In each trial, both blue cursors begin in the center of their respective bars (grey) and players must position them inside the pink targets. Targets are acquired by staying within them for a dwell time, depicted on each target as it fills in green (top target in Fig. 1-b). Players switch control between top and bottom cursors with a co-contraction impulse, synonymous with switching between grip aperture and wrist rotation when using a prosthesis. The trial is complete once both targets are acquired.

All software ran on a laptop connected to an external display that was positioned approximately 2 feet in front of participants. Participants sat in an office chair and were instructed to use the chair's adjustable armrests to maintain a comfortable and natural arm position for the duration of training. The armband was oriented consistently across all participants and sessions according to the manufacturer suggested best-practices (as worn in Fig. 1-c).

After positioning the armband and waiting five minutes to allow its sensors to stabilize to the participant's skin

TABLE I
30-MINUTE TRAINING SESSION SCHEDULE

Duration (min)	Activity	Description
5	Armband Calibration	Participants positioned armband on their dominant forearm orienting according to manufacturer's suggested best-practices (Fig. 1-c) and waited 5 minutes to allow sensors to stabilize to skin temperature and humidity. The experimenter then led participants through Momo's in-game calibration wizard, where participants mirrored a series of on-screen hand gestures to identify ideal calibration settings (full details in text). Settings were then verified through manual inspection.
20	Momo	Participants played *Momo*, a myoelectric training game. Rounds of play began 10 levels below the average achieved in the previous training session.
3	MyoFitts	Participants completed MyoFitts, consisting of 36 2-dof Fitts targeting tasks. The same 72 Fitts configurations were used across all participants, but presentation order was randomized in each session.
2	Daily Questionnaire	Participants complete a session-concluding daily questionnaire which includes an adapted NASA-TLX and Likert-style questions on perceived enjoyment and improvement.

temperature and humidity, a calibration session was performed to identify which two of the available eight sensors were best positioned to be used for two-site differential proportional control (i.e., to detect wrist flexor and extensor muscle contractions). This calibration was performed using the in-game calibration wizard provided with Momo [31]. The experimenter led participants through calibration, during which the software assigned sensor mappings and sensitivity settings for flexion and extension signals by selecting the sensor that read the highest signal for each of the two movements. Manual inspection of the muscle sites and an on-screen signal visualization tool were then used to verify the calibration, and sensitivity settings were adjusted as necessary to allow participants to achieve the full range of proportional input with a comfortable muscle contraction (full calibration details available in the calibration guide accompanying [31]). Consistent calibration settings were used across the Momo game and MyoFitts assessment tool to ensure identical control between applications. Calibration was performed at the beginning of each session to account for differences in armband sensor placement and skin impedances between sessions.

C. Procedure

Each training session lasted approximately 30 minutes and consisted of the same sequence of activities. The first and tenth sessions included an additional demographics and post-study questionnaire, respectively. Informed-consent was given at the beginning of the first session when participants agreed to the study procedure and were informed that they were free to withdraw from the study at any point. Table I presents a timeline of activities conducted during each training session. By design, Momo was intended to be the primary training tool under investigation, while MyoFitts was meant to capture a snap-shot performance assessment at the conclusion of each session. This is reflected by the substantially longer period of time spent with Momo compared to MyoFitts during training.

Throughout the sessions, participants were instructed to contract naturally with a comfortable and repeatable level of intensity. At the beginning of the MyoFitts task, participants were instructed to acquire targets as quickly and accurately as possible. Breaks (∼1 min) were offered between each round of Momo and before beginning MyoFitts, and were taken by participants at their discretion. Participants were provided with feedback and encouragement regarding commonly observed issues with their control during Momo gameplay (e.g., pointing out unintentional muscle co-contraction and explaining why this is an undesirable quality), but no intervention occurred while completing the MyoFitts tasks. The experimenter left the room while participants completed per-session questionnaires.

D. Design

The purpose of this study was to investigate how improvements in myoelectric control develop beyond the number of training sessions completed in many previous studies. Performance and improvement were assessed in several different ways, including in-game performance (i.e., specific to training activity), performance with muscle-control, and performance while completing a myoelectric targeting task, each of which are discussed in more detail below.

1) In-Game Performance: Average game-level achieved was used to assess in-game performance since Momo (the training game used) naturally progresses through a series of faster and more challenging levels. In each session, participants started rounds of play at a level of difficulty (i.e., platform rise speed) appropriate for their current abilities (computed as 10 levels lower than the average level achieved in their previous session). This resulted in 3-5 rounds of play per training session and ensured that an accurate representation of their performance was captured at a fun, engaging, and appropriate level of difficulty.

When calculating average game-level achieved, only rounds of gameplay in which the participant achieved more than 200 points (i.e., approximately 30s of gameplay) were included. This restriction was introduced to ensure that unrepresentative rounds of play did not skew results (e.g., experimenter accidentally clicked "Start Game" button).

2) Performance With Muscle Control: Performance with underlying muscle control was assessed using metrics developed to quantify control signal quality [30]. These metrics were computed offline using EMG control data logged at 60Hz by both the Momo and MyoFitts tools and are presented in Table II. Every row in the EMG log was labelled as belonging to one of three periods according to the participant's behavior at that point in time: 1) *calibration* – readings captured during initial armband calibration, 2) *proportional control* – readings captured during left/right movement in Momo or MyoFitts, or 3) *impulse* – readings captured during a co-contraction mode-switch. Each metric is computed using data from only one of these periods. The metrics are briefly

TABLE II

METRICS USED TO ASSESS MYOELECTRIC MUSCLE CONTROL

<table>
<tr><th>Metric</th><th>Focus</th><th>Period of EMG Log</th><th>Description</th><th>Motivation</th></tr>
<tr><td>Calibration Amplitude</td><td>Muscle Strength</td><td>Calibration</td><td>The level of contraction intensity, corresponding to the raw signal amplitude acquired from the armband during calibration. Larger is better.</td><td>Strong contractions minimize the impact of unintentional co-contractions, crosstalk, and other signal noise, and facilitate a wide range of proportional input.</td></tr>
<tr><td>Isolation</td><td>Proportional Control</td><td>Flexion / Extension</td><td>Ratio of intentional muscle contraction to involuntary muscle co-contraction. Computed independently for periods of flexion and extension, then averaged across the two. Larger is better.</td><td>Unintentional co-contractions lead to ambiguity in the myoelectric input signal, and in some control schemes work directly against the intended movement. Better muscle isolation leads to more effective use of proportional control.</td></tr>
<tr><td>Over-Exertion</td><td>Proportional Control</td><td>Flexion / Extension</td><td>A weighted tally of readings with amplitudes that exceed the calibrated 100% limit. Computed independently for flexion and extension, then averaged across the two. Smaller is better.</td><td>Exerting muscle contractions that are stronger than strictly necessary to achieve accurate control can lead to premature fatigue and muscle soreness. Learning to reliably create muscle contractions of an appropriate strength can lead to increased endurance when using a myoelectric device.</td></tr>
<tr><td>Speed Distribution</td><td>Proportional Control</td><td>Flexion / Extension</td><td>A measure of deviation from uniform use of proportional contraction strengths. Calculated by binning EMG readings by contraction strength, then summing the absolute difference between expected and actual occurrence counts in each bin. Smaller is better (i.e., smoother).</td><td>Research [3] suggests that the most successful myoelectric users are those who make use of the full proportional range of myoelectric input. Learning to accurately create contractions of varying strengths allows myoelectric users to operate their device at a variety of speeds.</td></tr>
<tr><td>Amplitude</td><td>Mode-Switch Trigger</td><td>Impulse</td><td>The height of the impulse "peak". Computed independently for flexion and extension, then averaged across the two. Larger is better.</td><td>Mode-switch triggers are registered by the myoelectric device when the flexion and extension signals simultaneously exceed a threshold. Strong impulses (i.e., large amplitude), allow reliable impulse detection.</td></tr>
<tr><td>Phasing</td><td>Mode-Switch Trigger</td><td>Impulse</td><td>The time difference (ms) between the peak of the flexion and extension signals during an impulse. Smaller is better.</td><td>Since the "impulse" mode-switching trigger requires both the flexion and extension signals to simultaneously exceed a certain threshold, having both signals peak at the same time increases the reliability of detection.</td></tr>
<tr><td>Width</td><td>Mode-Switch Trigger</td><td>Impulse</td><td>The duration of time (ms) between onset and conclusion of impulse. Smaller is better.</td><td rowspan="3">Myoelectric devices continuously interpret flexion and extension signals as hand open/close or wrist pronation/supination instructions, even when the user performs a mode-switch impulse. Creating shorter impulses reduces the opportunity for these signals to result in unintentional movement.

Specifically, reducing the "rise-time" of an impulse minimizes unintentional movement in the degree-of-freedom which is no longer being controlled, reducing the need for the user to "switch back and correct".</td></tr>
<tr><td>Rise</td><td>Mode-Switch Trigger</td><td>Impulse</td><td>The duration of time (ms) between onset and registration of impulse. Smaller is better.</td></tr>
<tr><td>Fall</td><td>Mode-Switch Trigger</td><td>Impulse</td><td>The duration of time (ms) between registration and conclusion of impulse. Smaller is better.</td></tr>
<tr><td>Fit</td><td>Mode-Switch Trigger</td><td>Impulse</td><td>The area between the flexion and extension signal curves. Smaller is better.</td><td rowspan="3">Since only the difference between flexion and extension signal amplitudes contributes to device movement, creating impulses where the two signals mirror one another can also reduce unintentional movement while creating mode-switch triggers.

Similar to "rise-time" mentioned above, impulses with a small "pre-fit" result in minimal movement in the degree-of-freedom no longer being controlled, reducing the need for the user to "switch back and correct".</td></tr>
<tr><td>Pre-Fit</td><td>Mode-Switch Trigger</td><td>Impulse</td><td>The area between flexion and extension curves, restricted between impulse onset and registration. Smaller is better.</td></tr>
<tr><td>Post-Fit</td><td>Mode-Switch Trigger</td><td>Impulse</td><td>The area between flexion and extension curves, restricted between registration and conclusion. Smaller is better.</td></tr>
</table>

Metrics used to quantify the foundational muscle signal characteristics of strong myoelectric control. Developed in previous research [30], these metrics were identified based on the practical experience and intuition of therapists and clinical experts. This table provides a description of each metric, along with an explanation of how it quantifies an important aspect of proficient myoelectric control.

introduced in the remainder of this section, with full details available in Table II.[1]

Calibration Amplitude was measured as the average amplitude of contractions created during the calibration period at the beginning of each session, measured independently for flexion and extension contractions. While this approach does not capture the amplitude of a maximum voluntary contraction (MVC), it more accurately represents the characteristics of signals created during normal prosthesis use (see *Apparatus* above for calibration procedure, as well as the calibration guide accompanying [30] for further details).

Average *isolation*, *over-exertion*, and *speed distribution* were computed using all periods of proportional control within the EMG log by first computing each metric independently for flexion and extension contractions, then combining them by computing the mean.

Mode-switch specific metrics (introduced in Table II) were computed independently for each impulse detected in the EMG log, then averaged across all impulses that occurred in a session.

[1] Figs. 2 and 3 in [30] illustrate how the metrics respond throughout training.

TABLE III
QUESTIONS ADMINISTERED THROUGHOUT STUDY

Label	Freq.	Question	Format
Improve Daily	Per-Session	*I performed better today than I did last session.*	7-point Likert[1,2]
Improve General	Post-Study	*My muscle control improved over the training sessions.*	5-point Likert[1]
Improve Momo	Post-Study	*The game helped me improve my muscle control.*	5-point Likert[1]
Improve Continue	Post-Study	*My muscle control would continue to improve if I pursued further training.*	5-point Likert[1]
Plateau-Count	Post-Study	*How many training sessions did you complete before you felt like you reached a plateau/stopped improving?*	Numeric[3]

1. Likert scale: 1- Strongly Disagree, 5/7 – Strongly Agree.
2. All participants responded 4 – Neutral following the first training session.
3. Participants either provided a numeric response (i.e., 1-10) or indicated that they had not yet reached a plateau.

Outliers were removed on a per-session basis independently for each metric by removing scores from any session that was more than 2 standard-deviations from the normalized per-session mean. An average of *0.81 +/− 0.06* outliers were removed for any session-metric combination, and manual inspection of the data revealed that these outliers could be attributed to a substantial deviation in a participant's calibration settings compared to preceding / succeeding sessions.

3) Fitts Targeting Performance: Fitts law has been shown to accurately describe myoelectric targeting tasks [23], and, recently, Fitts metrics have been used to assess myoelectric targeting ability [12], [37]. In this study, we use Fitts throughput (a measure of overall targeting performance – see [23] for details), path-efficiency (the shortest, straight line distance to a target divided by the actual distance travelled by the cursor), and error-rate (the number of times a user enters, then exits a target without successfully acquiring it – normalized by the number of trials completed) to quantify performance in the MyoFitts targeting task.

4) Questionnaire Data: Participants completed a questionnaire following each training session with additional questions included after their final session. Questions administered focused on perceived improvement throughout training (Table III). Each question has been given a unique label (shown in Table III), that will be used to identify it in the Results and Discussion sections.

5) Data Analysis: Since relative levels of improvement were of more interest than a participant's absolute levels of skill, all results presented are first normalized on a per-participant basis (according to each participant's results in session 1) before being averaged across all participants in each of the ten sessions. This allows the extent of learning and improvement to be more easily compared between subjects.

To investigate whether significant improvements in myoelectric control occurred over the course of training, metric scores across sessions (1, 4 and 10) were compared using a repeated measures ANOVA (RM-ANOVA). Data were first confirmed to be normally distributed using the Shapiro-Wilks test. When RM-ANOVA results indicated significance, follow up t-tests (with Bonferroni correction) were used to compare scores from sessions 1 and 4, as well as sessions 1 and 10. This was done to highlight possible difference between our findings those previously reported using 4 or fewer sessions. Results were considered significant for p-values of less than 0.05, and all results are reported with their corresponding inter-participant standard error of mean (SEM).

Due to a technical issue, the Momo portion of training (i.e., game-levels achieved, 20-minute EMG log) was not recorded for one participant during session 3. However, all data from the MyoFitts portion of the training session was captured and recorded correctly. This participant was excluded from the calculation of average game-level achieved for that session, but all other metrics were computed from the MyoFitts portion of training and are included in the results presented.

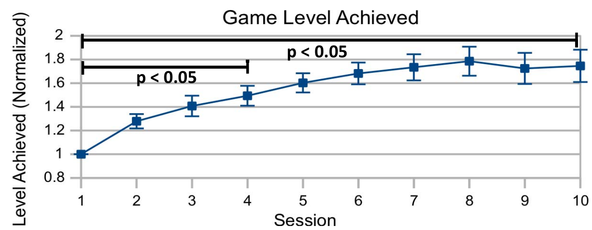

Fig. 2. Average in-game level achieved during training. Normalized per-participant, then averaged across all participants. Significantly higher in-game levels were achieved following both the forth, and tenth training session. Error bars indicate SEM.

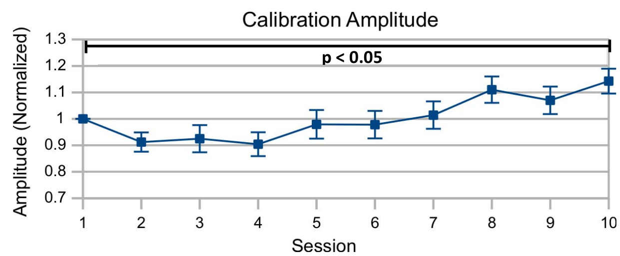

Fig. 3. Contraction strength during armband calibration. Normalized per-participant, then averaged across all participants. No significant improvements were observed at the forth training session, but participants created significantly stronger contractions after ten sessions. Error bars indicate SEM.

IV. RESULTS

A. In-Game Performance

In agreement with previous studies [6], [8], [9], [22], significant game-specific improvements were observed over the course of training (Fig. 2). Participants achieved significantly higher in- game levels after completing the series of training sessions, progressing 78.4% +/− 8.6% further through gameplay in session 10 compared to session 1.

B. Improvement in Muscle Control

Significant improvements in the newly introduced muscle control metrics were also observed upon completion of training. Participants achieved a 14.3% +/− 4.7% increase in calibration amplitude (Fig. 3) and improved significantly in their

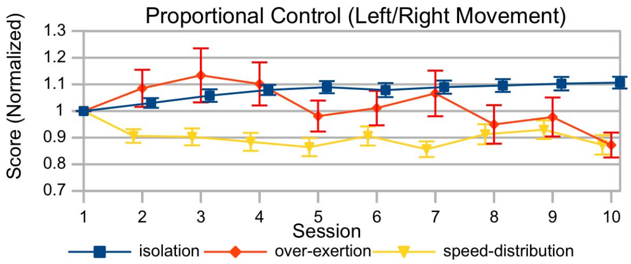

Fig. 4. Muscle-Control specific metric scores. Normalized per-participant, then averaged across all participants. Participants created more isolated contractions, with contraction-intensity distributed more evenly across the available amplitude band. Levels of significance between sessions 1 and 4, and sessions 1 and 10 can be found in Table IV. Error bars indicate SEM.

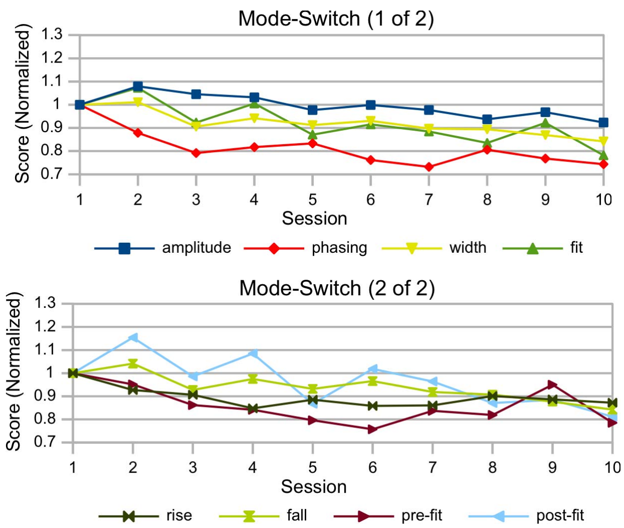

Fig. 5. Mode-Switch specific metric scores (Top: *Amplitude, Phasing, Width, Fit*, Bottom: *Rise, Fall, Pre-Fit, Post-Fit*). Normalized per-participant, then averaged across all participants. Error bars have been omitted for viewing clarity, however SEM values and significance are reported in Table IV.

levels of muscle isolation (Fig. 4). Significant improvements were also observed in phasing, rise, and pre-fit following the completion of training (Fig. 5). It should be noted, however, that no significant improvement was observed in three of the above-mentioned metrics after participants had completed the 4th session. A full breakdown detailing per-metric levels of improvement after completing the 4th and 10th training sessions is presented in Table IV.

C. Myoelectric Targeting in a Fitts Task

Significant improvements extended beyond the context of the Momo training game. Participants achieved a 72.8% +/− 2.8% decrease in error-rate while performing the MyoFitts targeting task, while increasing path-efficiency and throughput by 48.6% +/− 4.7% and 142.7% +/− 10.8% respectively, upon completion of training (Fig. 6).

D. Questionnaire Data

Improvements in muscle control were also reflected in questionnaire responses. Figures 7, 8, and 9 present questionnaire responses in detail. Participants reported feeling a small but consistent sense of improvement following each training session (Fig. 7 – Improve-Daily – 5.2/7.0). Participants also reported that they had improved over the course of training when reflecting back upon completion of the study (Fig. 8 – Improve-General – 4.7/5.0). Furthermore, 90% of

TABLE IV
IMPROVEMENTS IN MUSCLE METRIC SCORES

Metric	Session 4	Session 10
Calibration Amplitude	-9.6% (4.5%) *	+14.3% (4.7%)
Isolation	+7.9% (1.9%)	+10.7% (2.2%)
Over-Exertion	-10.2% (8.1%)	+12.8% (4.7%)
Speed Distribution	+11.6% (3.4%)	+12.7% (3.6%)
Amplitude	+3.2% (3.7%)	-3.1% (3.4%)
Phasing	+18.3% (7.2%)	+25.3% (6.2%)
Width	+5.8% (3.4%)	+8.5% (3.9%)
Rise	+15.2% (2.7%)	+10.7% (2.6%)
Fall	+2.5% (4.2%)	+8.5% (4.8%)
Fit	-0.5% (10.1%)	+17.3% (6.7%)
Pre-Fit	+15.9% (6.4%)	+21.2% (6.2%)
Post-Fit	-8.5% (11.3%)	+12.5% (9.1%)

Average level of improvement observed after completing 4 and 10 training sessions. Each entry indicates the percent of improvement since session 1 (positive – improvement, negative – degradation) and the inter-participant SEM in parenthesis. White cells indicate significant improvement ($p < 0.05$), while shaded cells indicate insignificance ($p >= 0.05$). Shaded cells with an asterisk (*) indicate a significant degradation in performance ($p < 0.05$).

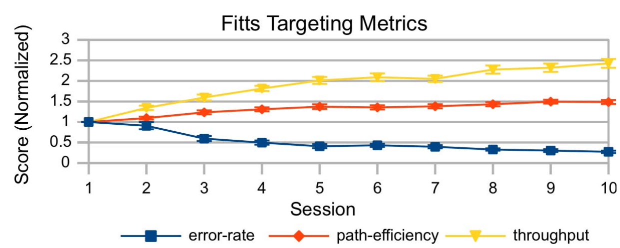

Fig. 6. Performance in MyoFitts across training sessions. Normalized per-participant, then averaged across all participants. Participants achieved improved throughput, path-efficiency, and error-rates after training. Significant levels of improvement were observed between sessions 1 and 4, and sessions 1 and 10 for all three metrics. Error bars indicate SEM.

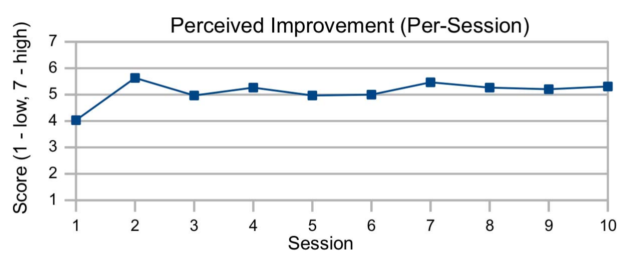

Fig. 7. Mean per-session questionnaire responses (Improve-Daily). Participants consistently reported feeling a sense of improvement from one session to the next throughout the study. All participants were instructed to respond with “4 – Neutral” following the session 1, since they could not yet refer back to the previous day of training.

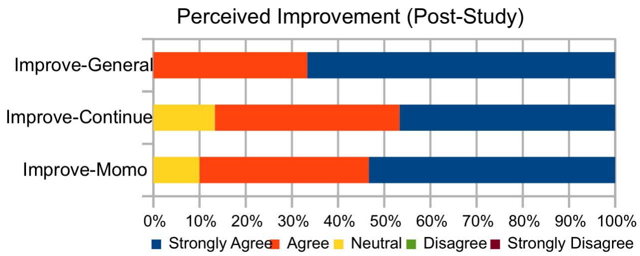

Fig. 8. Mean post-study questionnaire responses (*note that no one responded with Strongly Disagree or Disagree*). All participants agreed that they had improved throughout training (Improve-General), and 90% of participants attributed this improvement to the Momo game specifically (Improve-Momo). Furthermore, 87% of participants felt they would continue to improve if given the opportunity to continue training (Improve-Continue).

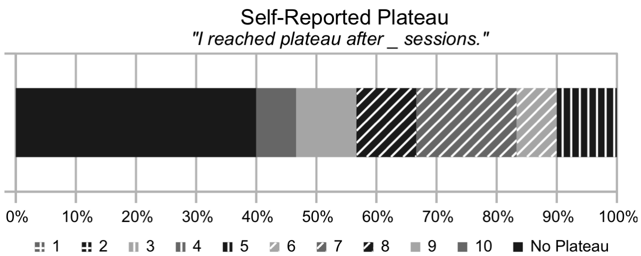

Fig. 9. Mean post-study questionnaire responses (*note that no one reported reaching a plateau earlier than after completing 5 training sessions)*. 40% of participants reported that they had not yet reached a plateau in improvement upon completion of the study (Plateau-Count).

participants attributed this improvement to the training game (Fig. 8 – Improve-Momo – 4.4/5.0). Even after completing ten sessions, however, 87% of participants felt that they would continue to improve if given the opportunity to complete further training (Fig. 8 – Improve-Continue), and no one reported feeling like they had achieved a plateau in improvement before the completion of their 5th training session (Fig. 9 – Plateau-Count).

V. Discussion

A. Gradual, Continual Progress and Improvement

The results of this work suggest that progress made in underlying muscle control develops more gradually than has generally been anticipated in previous myoelectric training research. Whether by intentional design, or due to unavoidable practical limitations, many previous studies have subjected trainees to only four or fewer training sessions [4], [5], [8], [9], [22], [33], [35], [36], [38]. Surprisingly, however, in our study not a single subject reported reaching a perceived plateau in performance earlier than their 5th training session. Similarly, participants reported small, consistent improvements in muscle control after each training session, however, 87% believed they would continue to improve beyond the 10th session if given the opportunity to continue training. Performance metric scores reinforce this finding as improvements were observed in the metrics at varying rates. While improvements in two metrics materialized early in training (isolation, rise), three others did not show significance until training was complete (calibration amplitude, phasing, pre-fit – Table IV). Furthermore, three additional metrics (speed distribution, width, and fit) trended towards improvement, although not at the significant level, and may have shown improvement had even more training been conducted.

These results are a reminder that learning myoelectric control is a gradual, difficult, and complex process. Taken together, they suggest that assessing performance at early stages of myoelectric training may not be a reliable or representative indicator of how an individual will perform after lengthier amounts of training, such as through the prolonged use of a prosthesis. While the slope of the learning curves may differ with different training activities, it is likely that the gradual, continual nature of improvement is something inherent in myoelectric control, just as has been demonstrated in other complex motor-control tasks such as throwing darts [16], serving a volleyball [32], or rolling cigars [7] (see [18] for more examples). The gradual and continual development of myoelectric muscle control has also been observed in a recent study exploring the use of spatially-coded electrotactile feedback [29]. This work agrees with our findings, further suggesting that users do not reach a performance ceiling as quickly as has been assumed in previous research.

B. Reconsidering the Benefits of Training Activities

As many previous studies have only assessed skill transfer after training for relatively short periods [4], [5], [8], [9], [22], [33], [35], [36], [38], our results suggest that further work is needed to better understand the potential benefits of training activities. The fact that improvement has previously been observed in training activities, but not in transfer to functional tasks, has led some to believe that there is no benefit to such training activities. However, given our findings, it is possible that participants in these shorter studies may have had insufficient time realize the benefits of training.

While the current work stops short of demonstrating functional transfer, it does caution that improvements in the training activity (such as improvement in a game) can occur more rapidly than potential underlying improvements in control. This might be expected as the game task involves strategy, meaning that players can learn behavioral tricks to advance farther in the game. This work suggests that this behavioral optimization may occur before receiving measurable benefits related to the underlying myoelectric control strategy. This may also be the case for other non-game training activities. Investigating these possibilities will be an important direction of our ongoing and future work.

C. Games Enable Engagement During Training

Several previous studies have presented conflicting results with respect to the possible value of training games [6], [8], [9], [22]. Considering our findings, it is possible that discrepancies between these previous studies may be a consequence of the relatively short series of training sessions completed by participants. Our results remind us that muscle control does indeed improve through continued practice and training, and that carefully designed games can provide therapeutic value.

While functional transfer has been given heavy emphasis in previous studies [8], [9], [35], [36], therapists and clinical experts often do not use (*or envision using*) muscle training games for this purpose. In clinical practice, 'games' are predominately used in early, pre-prosthetic, training where therapeutic goals include identification and strengthening of muscle sites as well as the development of the foundational skills required to succeed with myoelectric control [3], [28]. Judging games on their ability to create direct and immediate functional improvements may therefore not necessarily be clinically accurate or relevant.

Well-designed games can also create an engaging and motivating environment that patients need to achieve success. While lack of participant engagement and motivation to continue training have been identified as limiting factors when attempting to complete a longer series of training sessions in the past [33], we completed this study with zero participant attrition (one subject withdrew after 8 sessions, but for unrelated reasons). In fact, several participants continued training beyond the 10-session series simply because they wanted to beat their previous high scores. This demonstrates the value and importance that well-designed game-based tools can bring to both myoelectric training and research.

VI. Future Work

The focus of this research was to explore how foundational aspects of muscle control develop over time. To accomplish this, we developed and introduced metrics to quantify and assess muscle control skill and underlying control signal quality. The design of these metrics was based on the experience and expertise of clinical therapists who specialize in myoelectric training with amputees [30]. Consequently, they attempt to quantify the characteristics of muscle control that therapists already identify as indicators of proficient myoelectric control (see the "Motivation" column of Table II for details) [22], [28], [31]. However, it is left to future work to perform a rigorous validation of these metrics in a clinical setting to test how they relate to functional prosthesis use.

This study employed two-site proportional myoelectric control and co-contraction mode-switching, as this type of control is commonly used by the patients of our local prosthetics clinic. As a result, the metrics were designed to quantify aspects of muscle control considered to be important for these control schemes. Many variants of conventional proportional control exist in practice, however, and pattern-recognition based controls are now emerging as clinically viable options [10], [11], [13], [23], [24], [26], [37]. While advances in control schemes and dexterous prostheses (such as the Michelangelo hand [19]) may mitigate some limitations of two site proportional control, we believe that any myoelectric control scheme should benefit from improved fundamental muscle control. This extension to other control schemes, including pattern recognition, is a current and ongoing focus.

Finally, while Momo was intended as the training tool in this study, the regular use of MyoFitts for performance assessment may have also contributed to user learning. Without a dedicated control group, their relative effects cannot be quantified. Nevertheless, these results demonstrate improvements in muscle control developing through continued use of myoelectric controlled tasks, whether it be from the Momo game of MyoFitts evaluation tool. Interestingly, even within this study group, improvements occurred at widely varying rates. Further exploration of how performance and improvement vary with tools and training environments could lead to a better understanding of how these improvements occur, as well as how to optimize learning curves.

VII. Conclusion

In this study, 30 novice myoelectric control participants were followed as they completed a series of ten 30-minute game-based myoelectric muscle training sessions. Participants achieved significant improvements in foundational aspects of muscle control. However, this improvement occurred more gradually than has been anticipated in previous research. While we do not provide a definitive recommendation for the number of training sessions required (as learning rates may differ for different training activities), the gradual and continual nature of improvement is likely inherent in learning myoelectric control, as is the case when learning many other complex motor-control skills. Our findings provide evidence supporting the therapeutic value in muscle training games, and stress the importance of adequate, relevant myoelectric training in both research and clinical settings.

References

[1] E. A. Biddiss and T. T. Chau, "Multivariate prediction of upper limb prosthesis acceptance or rejection," *Disability Rehabil. Assistive Technol.*, vol. 3, no. 4, pp. 181–192, 2008.

[2] E. A. Biddiss and T. T. Chau, "Upper limb prosthesis use and abandonment: A survey of the last 25 years," *Prosthetics Orthotics Int.*, vol. 31, no. 3, pp. 236–257, 2007.

[3] H. Bouwsema, C. K. van der Sluis, and R. M. Bongers, "Guideline for training with a myoelectric prosthesis," Ph.D. dissertation, Dept. Rehabil. Med., Center Human Movement Sci., Univ. Med. Center Groningen, Univ. Groningen, Groningen, The Netherlands, 2013.

[4] H. Bouwsema, C. K. van der Sluis, and R. M. Bongers, "Learning to control opening and closing a myoelectric hand," *Arch. Phys. Med. Rehabil.*, vol. 91, no. 9, pp. 1442–1446, 2010.

[5] H. Bouwsema, C. K. van der Sluis, and R. M. Bongers, "The role of order of practice in learning to handle an upper-limb prosthesis," *Arch. Phys. Med. Rehabil.*, vol. 89, no. 9, pp. 1759–1764, 2008.

[6] R. Clingman and P. Pidcoe, "A novel myoelectric training device for upper limb prostheses," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 4, pp. 879–885, Jul. 2014.

[7] E. R. F. W. Crossman, "A theory of the acquisition of speed-skill," *Ergonomics*, vol. 2, no. 2, pp. 153–166, 1959.

[8] L. Van Dijk, C. K. van der Sluis, H. W. van Dijk, and R. M. Bongers, "Learning an EMG controlled game: Task-specific adaptations and transfer," *PLoS ONE*, vol. 11, no. 8, p. e0160817, 2016.

[9] L. Van Dijk, C. K. van der Sluis, H. W. van Dijk, and R. M. Bongers, "Task-oriented gaming for transfer to prosthesis use," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 12, pp. 1384–1394, Dec. 2016.

[10] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 7, pp. 848–854, Jul. 2003.

[11] A. Fougner, Ø. Stavdahl, P. J. Kyberd, Y. G. Losier, and P. A. Parker, "Control of upper limb prostheses: Terminology and proportional myoelectric control—A review," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 20, no. 5, pp. 663–677, Sep. 2012.

[12] E. N. Kamavuako, E. J. Scheme, and K. B. Englehart, "On the usability of intramuscular EMG for prosthetic control: A Fitts' law approach," *J. Electromyograp. Kinesiol.*, vol. 24, no. 5, pp. 770–777, 2014.

[13] D. F. Lovely, "Signals and signal processing for myoelectric control," in *Powered Upper Limb Prostheses*. Berlin, Germany: Springer, 2004, ch. 3, pp. 35–54.

[14] J. M. Malone *et al.*, "Immediate, early, and late postsurgical management of upper-limb amputation," *J. Rehabil. Res. Develop.*, vol. 21, no. 1, pp. 33–41, 1984.

[15] M. L. McCarthy, T. Ewashko, and E. J. MacKenzie, "Determinants of use of outpatient rehabilitation services following upper extremity injury," *J. Hand Therapy*, vol. 11, no. 1, pp. 32–38, 1998.

[16] P. V. McDonald, R. E. A. Van Emmerik, and K. M. Newell, "The effects of practice on limb kinematics in a throwing task," *J. Motor Behav.*, vol. 21, no. 3, pp. 245–264, 1989.

[17] (2017). *Thalmic Labs-Myo Armband*. Accessed: Jun. 22, 2017. [Online]. Available: www.myo.com

[18] A. Newell and P. S. Rosenbloom, "Mechanisms of skill acquisition and the law of practice," in *Cognitive Skills and Their Acquisition*, vol. 1. 1981, pp. 1–55. [Online]. Available: https://books.google.com/books/about/Cognitive_Skills_and_Their_Acquisition.html?id=7oEtr1KvMbgC

[19] R. C. Oldfield, "The assessment and analysis of handedness: The Edinburgh inventory," *Neuropsychologia*, vol. 9, no. 1, pp. 97–113, 1971.

[20] 2017. *Ottobock Prosthestics*. Accessed: Jun. 22, 2017. [Online]. Available: www.ottobock.com

[21] P. A. Parker and R. N. Scott, "Myoelectric control of prostheses," *Crit. Rev. Biomed. Eng.*, vol. 13, no. 4, pp. 283–310, 1985.

[22] C. Prahm, L. Vujaklija, F. Kayali, P. Purgathofer, and O. C. Aszmann, "Game-based rehabilitation for myoelectric prosthesis control," *JMIR Ser. Games*, vol. 5, no. 1, p. e3, 2017.

[23] E. J. Scheme and K. B. Englehart, "Validation of a selective ensemble-based classification scheme for myoelectric control using a three-dimensional Fitts' law test," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 4, pp. 616–623, Jul. 2013.

[24] E. Scheme and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use," *J Rehabil. Res. Develop.*, vol. 48, no. 6, pp. 643–660, 2011.

[25] SHAP. (2017). *The Southampton Hand Assessment Procedure*. Accessed: Jun. 22, 2017. [Online]. Available: www.shap.ecs.soton.ac.uk

[26] A. M. Simon, B. A. Lock, and K. A. Stubblefield, "Patient training for functional use of pattern recognition-controlled prostheses," *J. Prosthetics Orthotics*, vol. 24, no. 2, p. 56, 2012.

[27] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, "The target achievement control test: Evaluating real-time myoelectric pattern recognition control of a multifunctional upper-limb prosthesis," *J. Rehabil. Res. Develop.*, vol. 48, no. 6, p. 619, 2011.

[28] L. M. Smurr, K. Gulick, K. Yancosek, and O. Ganz, "Managing the upper extremity amputee: A protocol for success," *J. Hand Therapy*, vol. 21, no. 2, pp. 160–176, 2008.

[29] M. Štrbac *et al.*, "Short- and long-term learning of feedforward control of a myoelectric prosthesis with sensory feedback by amputees," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 9, pp. 2133–2145, Nov. 2017.

[30] A. Tabor, W. Hill, S. Bateman, and E. Scheme, "Quantifying muscle control in myoelectric training games," in *Proc. Myoelectr. Control Symp. (MEC)*, vol. 4. Fredericton, NB, Canada, 2017, pp. 1–4.

[31] A. Tabor, S. Bateman, E. Scheme, D. R. Flatla, and K. Gerling, "Designing game-based myoelectric prosthesis training," in *Proc. CHI Conf. Human Factors Comput. Syst.*, Denver, CO, USA, 2017, pp. 1352–1363.

[32] J. Temprado, M. Della-Grasta, M. Farrell, and M. Laurent, "A novice-expert comparison of (intra-limb) coordination subserving the volleyball serve," *Human Movement Sci.*, vol. 16, no. 5, pp. 653–676, 1997.

[33] B. Terlaak, H. Bouwsema, C. K. van der Sluis, and A. R. M. Bongers, "Virtual training of the myosignal," *PLoS ONE*, vol. 10, no. 9, p. e0137161, 2015.

[34] M. Vilarino *et al.*, "Outcomes and perception of a conventional and alternative myoelectric control strategy: A study of experienced and new multiarticulating hand users," *J. Prosthetics Orthotics*, vol. 27, no. 2, pp. 53–62, 2015.

[35] D. L. Weeks, D. I. Anderson, and S. A. Wallace, "The role of variability in practice structure when learning to use an upper-extremity prosthesis," *J. Prosthetics Orthotics*, vol. 15, no. 3, pp. 84–92, 2003.

[36] D. L. Weeks, S. A. Wallace, and D. I. Anderson, "Training with an upper-limb prosthetic simulator to enhance transfer of skill across limbs," *Arch. Phys. Med. Rehabil.*, vol. 84, no. 3, pp. 437–443, 2003.

[37] S. M. Wurth and L. J. Hargrove, "A real-time comparison between direct control, sequential pattern recognition control and simultaneous pattern recognition control using a Fitts' law style assessment procedure," *J. Neuroeng. Rehabil.*, vol. 11, no. 1, p. 91, 2014.

[38] H. K. Yuen, D. L. Nelson, C. Q. Peterson, and A. Dickinson, "Prosthesis training as a context for studying occupational forms and motoric adaptation," *Amer. J. Occupat. Therapy*, vol. 48, no. 1, pp. 55–61, 1994.

2018-07-12

Evaluation of myoelectric control learning using multi-session game-based training

Tabor, Aaron

IEEE

https://doi.org/10.1109/TNSRE.2018.2855561