QUANTIFYING MUSCLE CONTROL IN MYOELECTRIC TRAINING GAMES

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ABSTRACT

Myoelectric training games have recently gained interest for increasing motivation and engagement when learning prosthetic control. However, game-based training has not yet been shown to result in improved performance of functional tasks, which has led to a push for "task-similar" training exercises and a questioning of the merit of training games altogether. This apparent lack of observable skill transfer remains counterintuitive, because games can encourage movements similar to those required for prosthesis control. To better understand the effects of game-based training, we identify a set of 'muscle-control metrics' to quantify characteristics of EMG control input that are considered important for 2-site proportional control. In this paper, we introduce these muscle-control metrics and describe a myoelectric training game developed in collaboration with patients and clinicians that is able to capture metrics during gameplay. We also outline an on-going data collection study, which will allow us to identify which aspects of a myoelectric training game lead to improvements in input signals.

INTRODUCTION

To take advantage of muscle plasticity and maximize potential for success, it is desirable for new myoelectric prosthesis users to begin training as early as possible following amputation (early childhood in the case of congenital limb-difference) [1]. However, a delay is often incurred before patients receive their prosthesis due to factors including recovery time, insurance processing, and fabrication and fitting of the prosthesis, and muscle training tools are used to keep patients active while waiting. However, these activities are often monotonous or lack sufficient feedback, making it difficult for patients to stay motivated [8].

Game-based training tools have been proposed to address the loss of motivation that patients often experience [3,4,5,7]. Muscle-controlled games can provide an engaging experience, making the otherwise monotonous training exercises more enjoyable. Therapists and prosthetists consider training games – and the muscle improvements they create – to be a valuable part of the training process. In practice, even simple games are used early in training to improve understanding, strength, and endurance, without the expectation of achieving functional skill transfer [7].

Despite their widespread use in practice, skills acquired in games have not been shown to transfer to functional prosthetic control, leading some researchers to question the benefit of training games altogether [3,4]. These studies, however, have only looked at coarse game performance (e.g., levels and score) as an indicator of learning, so the reasons *why* success in muscle-controlled training games does not predict improved functional control is still unclear.

To address the lack of information about the nature of improvement in training games and in myoelectric control, we propose a set of *muscle-control metrics* for assessing skill during the pre-prosthetic phase of myoelectric training. These metrics, inspired through conversations with clinicians, more accurately assess performance by quantifying aspects of muscle control that are important for success with a prosthesis. We built the ability to quantify and track these metrics into a training game we previously created through a user-centered design process with patients and clinicians [7].

Our work makes two main contributions: 1) we provide a set of objective and measurable metrics for tracking and assessing changes in muscle control; and, 2) we provide a freely available training game that enables the collection of these new muscle-control metrics. In the remainder of this paper, we describe work on game-based training for myoelectric control, introduce our muscle-control metrics, present our training game, and finally, outline our ongoing data collection that will allow us to better understand the nature of skills acquired through training games and how they might transfer to functional control.

BACKGROUND

Myoelectric Training Games

Recent research on training games has shown conflicting results. One study, employing the PAULA

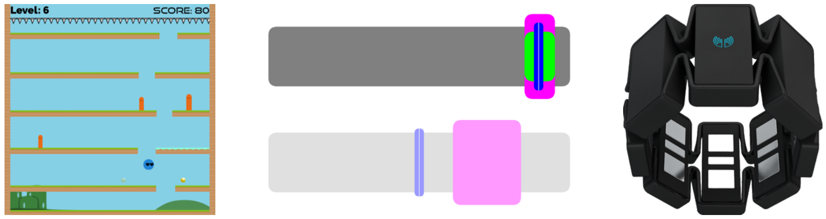

Figure 1: Research Tools. a) The Falling of Momo: Myoelectric Muscle-Training Game (github.com/hcilab/Momo.git), b) MyoFitts: Myoelectric 2-DOF Fitts Test (github.com/hcilab/MyoFitts.git), c) Myo Armband: Myoelectric Device (myo.com)

software suite, found that game-based tools are just as effective as traditional training approaches and that clinicians and patients can use games and other training activities interchangeably [2]. Conversely, follow-up studies by the same authors have suggested that some training games may be no more effective than a total lack of training. This recent work has suggested that, while patients might acquire skills in the game, they may not translate to improvements in prosthesis control [3,4]. These conflicting results suggest that the specific challenges associated with designing training games for amputees are not fully understood.

Outcome Measures

Assessing a patient's myoelectric ability is crucial for tracking progress over time. Existing measures are divided into two categories: 1) observational, and 2) self-reported [9]. *Observational measures* focus on quantitative, functional metrics such as task completion time, while *self-reported data* tend to focus on subjective elements such as perceived usefulness and embodiment of a prosthesis. Although an important focus during clinical training, muscle signal quality - an underlying prerequisite for robust myoelectric control – is often overlooked in existing observational metrics.

GAMES AND TRAINING ACTIVITIES

To support our research in training games, we have developed a game, called the *The Falling of Momo* (Figure 1a), and a standalone training activity based on acquiring targets, called *MyoFitts* (Figure 1b).

Momo is a muscle training game in which the player (blue) navigates their descent through a series of continually rising platforms [7]. Momo's design was aimed at creating a fun and engaging game that requires muscle movements that align with those required in prosthetic control. Flexion and extension contractions move Momo left and right, while a mode-switch co-contraction causes him to jump. Momo's features and design were informed and iteratively developed throughout a user-centered design process. Our process engaged amputee patients and clinicians through play testing and interviews, which we iteratively used to refine our game. Our work (described in [7]) proposes a set of design requirements for building training games that best meet the needs of patients and clinicians.

MyoFitts is a myoelectric targeting test with similar controls. Flexion and extension contractions moves the cursor (blue) into the targets (pink: un-acquired, green: acquired), with mode-switching being used to change focus between bars. Unlike Momo, MyoFitts is not a game, but instead is a training activity used in myoelectric control research (e.g., [6]).

Both Momo and MyoFitts are controlled with a 2-site proportional control strategy using the Thalmic Labs Myo Armband (Figure 1c), a commercially available myoelectric input device, which we have previously assessed as viable for use in training [7]. Both Momo and MyoFitts are freely available tools (see links in Figure 1) that incorporate data collection based on the muscle-control metrics outlined below.

MUSCLE-CONTROL METRICS

The following metrics are proposed for quantifying muscle control ability and are derived from logs of the EMG data captured during game play.

Muscle-Control Metrics

Several metrics are proposed to quantify common characteristics of muscle signals that are beneficial for all aspects of 2-site proportional control.

Isolation: When using a prosthesis with difference-based proportional control, greater muscle isolation enables a wider range of proportional speeds.

Isolation is computed as the ratio of intentional to unintentional muscle activity. It is calculated by inferring the intended direction of motion (i.e., stronger of the 2 EMG readings), and dividing by the level of unintentional co-contraction (i.e., the weaker of the 2

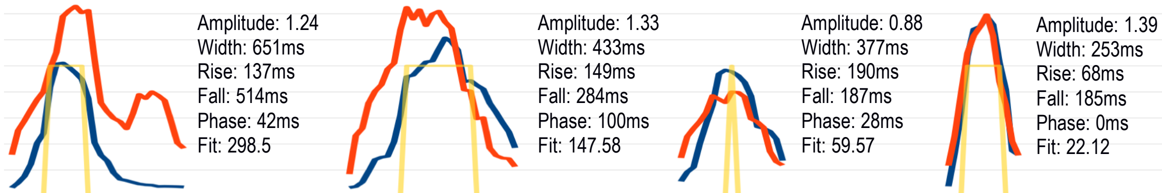

Figure 2: Co-contraction Improvements. Each co-contraction depicted was generated by a single participant during a series of 4 pilot training sessions (leftmost: session 1, rightmost: session 4). Red and blue lines represent flexion and extension signals, respectively, while yellow spikes indicate periods when the training system detected a mode-switch. Metric scores are shown to the upper-right.

EMG readings). Periods of impulse (described below) and rest (i.e., both readings below a threshold) are excluded. *Higher is better.*

Over-Exertion: Learning to create muscle contractions of an appropriate strength helps patients increase endurance while using a prosthesis.

Over-exertion is the weighted-tally of all EMG readings above the calibrated maximum voluntary contraction level, averaged by the number of samples. Higher values reflect unnecessarily strong contractions. Periods of rest are excluded. *Lower is better.*

Mode-Switch Metrics

Accurate co-contractions allow a prosthesis user to mode-switch reliably, limiting unintentional device movement. Mode-switching, however, is often a source of frustration, even for experienced prosthesis users [8]. Therefore, many of our metrics focus specifically on mode-switching and are calculated over brief periods of co-contraction. Co-contractions are detected by first identifying the registration time of each mode-switch, then searching forwards and backwards through the log for onset and conclusion times of the co-contraction, respectively (Figure 3, right). Figure 3 introduces terminology and demonstrates each of the metrics described below.

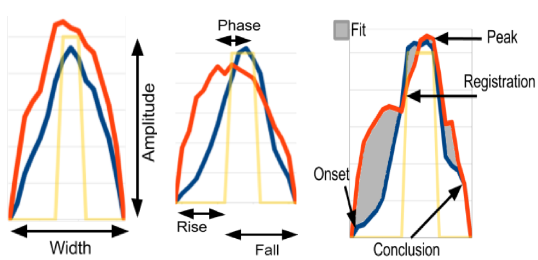

Figure 3: Terminology and Examples. Red and blue lines show the levels of flexion and extension muscle contraction, respectively. Yellow spikes indicate when the training system detected a mode-switch.

Amplitude: Mean height of flexion and extension signal peaks achieved during co-contraction. *Higher is better.*

Width: Duration of time between onset and conclusion of the co-contraction. *Shorter is better.*

Rise: Duration of time between onset and registration of the co-contraction. *Shorter is better.*

Fall: Duration of time between registration and conclusion of the co-contraction. *Shorter is better.*

Phase: Duration of time between the peaks of flexion and extension muscle signals during the co-contraction. *Shorter is better.*

Fit: Absolute difference in area between the flexion and extension signal curves during the co-contraction. *Smaller is better.*

In agreement with previous results [1,6], our pilot data suggests that game-based training can lead to improved muscle control and demonstrates how our metrics can be used to quantify and track these improvements (Figure 2).

DISCUSSION

Transfer to Improved Functional Performance

While our metrics are not yet clinically validated, they are based on principles of 2-site proportional control. Because of this, it is likely that they effectively characterize aspects of control not currently captured by coarser measures, such as scores in training games or completion times in functional assessment tasks.

We are currently running an experiment where new myoelectric users train using our game over a period of ten or more play sessions. In this experiment, we are tracking progress both in game play and through our muscle metrics, enabling a direct comparison between in-game learning and improvements in muscle control. Before participating in the study, all participants are briefed on study details and provide informed consent in agreement with the University of New Brunswick Research Ethics Board (REB 2017-047).

We believe that the metrics may also have further applications. Analyzing muscle-control improvement in detail allows clinicians to present patients with much more specific, targeted, and quantifiable training goals. Additionally, our metrics can be incorporated into games designed for at-home training and provide targeted feedback and increased awareness of progress made between clinical visits. Finally, our metrics are not specific to games; if EMG logs were collected from other activities (e.g., functional prosthetic tasks), the metrics obtained could be compared to those obtained during training games for discrepancies.

Limitations of the Current Muscle-Control Metrics

Some characteristics typically associated with strong myoelectric muscle control are not captured in our current metrics. Neither *consistency*, the ability to create and sustain a desired level of contraction strength, nor *endurance*, the ability to perform for prolonged periods of time without experiencing fatigue or performance degradation, are reflected in our metrics. Previous studies have assessed improvements in endurance by having participants perform a myoelectric tracking task both before and after training, recording the time at which participants became fatigued [6]. To our knowledge, improvements in consistency has not been assessed in the past.

When first learning myoelectric control, it is common for a patient to attempt a mode-switch several times before succeeding. Unsuccessful co-contractions (i.e., when the patient's attempt was not registered by the training system) hold valuable training information, but are not currently accounted for in our metrics. Incorporating these occurrences could help clinicians provide patients with even more constructive advice.

We observed in our pilots that, as participants got familiar with our training game, they began frequently "sliding into" and "sliding out of" mode-switches (i.e., quickly transitioning between left/right movement and jumps without relaxing muscles between the two phases). It is difficult to algorithmically distinguish between this "sliding" behavior and genuinely problematic impulses, so to avoid artificially inflating mode-switch metric scores we foresee the need to perform a more intelligent identification of mode-switches within EMG logs. It is interesting to question whether this "sliding" behavior is evidence of the development of a bad habit, or of a sense of proficiency and comfort with the control scheme.

CONCLUSION

In this work, we introduce a new set of metrics that are well suited to quantify improvement that occurs during myoelectric training games. We suggest that the information provided through these metrics is key to understanding skill transfer between training activities and functional control. Further, we believe our metrics would be beneficial to clinicians as they guide new patients through the training process, allowing them to identify specific deficits in control with greater precision. We have also demonstrated how the metrics can be employed and interpreted through their incorporation into a carefully designed training game, and a commonly used training activity. Our tools are freely available and may help provide critical new findings regarding skill transfer between game-based training activities and real-world prosthesis control.

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