A PRELIMINARY INVESTIGATION INTO BIO-INSPIRED DATA COLLECTION FOR TRANSHUMERAL TARGETED MUSCLE REINNERVATION PROSTHETIC CONTROL

Laura C. Petrich[1,5], Heather E. Williams[2,5], Matthew E. Taylor[1,5], Jacqueline S. Hebert[2,4], Pierre Lemelin[3], Ahmed W. Shehata[2], and Patrick M. Pilarski[4,5]

[1]*Dept. of Computing Science,* [2]*Dept. of Biomedical Engineering,* [3]*Dept. of Surgery, and* [4]*Dept. of Medicine, University of Alberta, Edmonton, AB, Canada;* [5]*Alberta Machine Intelligence Institute (Amii), Edmonton, AB, Canada.*

ABSTRACT

For persons with transhumeral amputation, targeted muscle reinnervation (TMR) has unlocked the potential for innovative and intuitive control of myoelectric prostheses. There are many open source datasets available for training machine learning (ML) models for transradial and transhumeral prosthetic control. However, to the best of our knowledge, no datasets have been gathered *in different limb positions* with the intent of training models specifically for *persons with transhumeral amputation who have undergone TMR surgery*. Moreover, such a dataset is challenging to curate as TMR is still a relatively new surgical technique and there are few people with TMR. In this work we present a novel biologically-inspired protocol for collecting data from *persons both with and without upper-limb amputations* that can be used to train generalized ML models for this growing population of users. Our results from a three-participant pilot study suggest that by choosing targeted sensor placements that correspond to specific limb nerve/muscle compartment associations post-TMR surgery, we can potentially capture control-relevant muscle activation patterns from persons without limb difference that closely resemble expectations of anatomical prime movers. We expect this collection protocol to provide further utility in studying the relationship between limb positions and myocontrol signals, and differences between isotonic and isometric muscle contractions during prosthesis use, leading to a new generation of TMR-ready control solutions.

INTRODUCTION

Most commercially available motorized prostheses are controlled via electromyogram (EMG) signals from a pair of residual agonist-antagonist muscles [1]. Conventional control strategies map the acquired EMG signal amplitude to operate each joint of the prostheses [2]. For example, EMG signals from the contraction of the biceps brachii and triceps brachii muscles can be mapped to operate elbow flexion and extension, respectively. However, myoelectric control with only two signals is slow and unintuitive [3]. In contrast, targeted muscle reinnervation (TMR) is a surgical technique that reroutes nerves that would innervate forearm and hand muscles to alternative muscle sites in the residual limb [4]. As a result, persons with TMR and transhumeral amputations (hereafter simply termed *users*) can have up to five distinct muscle sites, allowing for advanced ML solutions to control multiple joints simultaneously. TMR has been shown to improve myoelectric prosthesis control for persons with transhumeral amputations or shoulder disarticulations [5, 6].

Machine learning (ML) models for prosthetic control can be trained to recognize patterns in the acquired signals related to their physiologically appropriate joint action [7]. However, training a personalized ML model capable of making accurate predictions in different limb positions and conditions of use requires a substantial amount of labelled data from the user, which is time consuming and prohibitive during daily use [8]. Furthermore, these models tend to suffer from lack of generalizability both across and within participants, due to inter- and intra-participant variability, as well as differences in sensor placement and environmental conditions [2, 9]. Being able to augment the training set with data from persons without limb differences—or a TMR user's other limb without amputation—may contribute to both increasing the initial generality of learned controllers and reducing re-training effort. Our preliminary study demonstrates that data collected using our proposed protocol reflects anatomically-based expectations of muscle activation patterns for a non-amputated upper limb during various actions. This will enable future work to analyze the effect of limb positions on muscle activation signals and capture the differences between isotonic and isometric muscle contractions in the arm and forearm.

METHODS

Our proposed data collection protocol provides an anatomically-inspired sensor placement guide designed to acquire signals from muscles that align with a residual limb post-TMR. We first describe an overview of the data collection protocol and then present the results of a three-person pilot study.

Bio-inspired Sensor Placement

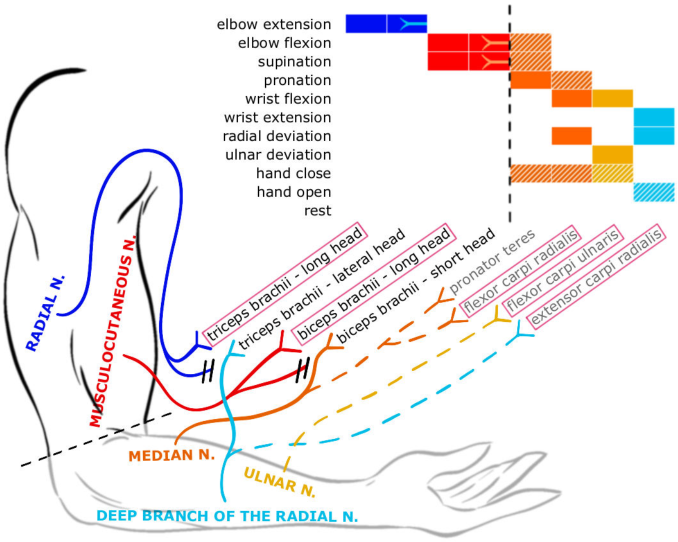


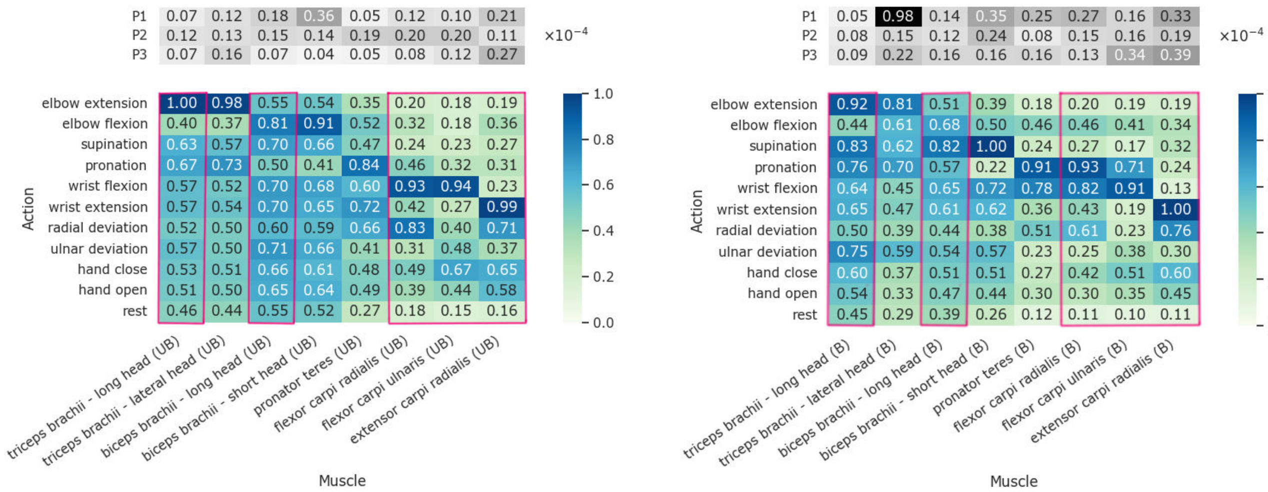
Figure 1: The five nerves responsible for providing motor innervation to muscles of the residual limb after transhumeral TMR. Note: N. denotes *nerve*; this figure is best viewed in colour.

Since we were interested in creating a data collection protocol that can be used on both prosthesis users and persons without limb difference, we took inspiration from our own underlying anatomy. While humans show some variation in the location of individual nerves, we all share the same basic innervation patterns, originating from the development of the limb buds, with each terminal nerve always innervating the same muscles [10]. The intermuscular septum divides the limb bud into anterior and posterior compartments, with flexor muscles developing in the former and extensor muscles in the latter [11]. The brachial plexus provides innervation to the upper limb and follows the same division, with trunks separating into anterior and posterior divisions before ending as five terminal branches. The axillary and radial nerves supply the posterior compartment while the musculocutaneous, median, and ulnar nerves supply the anterior compartment. For our protocol, we positioned sensors on specific muscles based on their nerve supply. In other words, muscles are viewed as a conduit for collecting motor signals from the brain, which we can then use as input features for training ML models. It is because of this novel perspective that we will be able to collect data from both users and persons without limb differences.

Figure 1 shows the five nerves responsible for providing motor signals to muscles in the residual limb after TMR surgery. The radial nerve natively innervates the long and lateral heads of the triceps brachii (marked by the dark blue lines in Figure 1); for users, the lateral head is denervated from the radial nerve (demarked by black slanted lines through the dark blue line) with the deep branch of the radial nerve re-routed to provide supply to the muscle belly (solid light blue line). Since the deep branch of the radial nerve natively supplies most of the posterior compartment of the forearm, for a person without limb differences, we can choose any muscle from this compartment to position the relevant sensor. We chose the extensor carpi radialis longus and brevis (dashed light blue line) due to its proximity to the surface and because it contributes to both wrist flexion and radial deviation. We follow the same reasoning for the remaining four nerves. The musculocutaneous nerve natively innervates the long and short heads of the biceps brachii (solid red line); for users, the median nerve is re-routed to the short head of the biceps brachii (solid orange line), which in turn natively supplies the pronator teres and flexor carpi radialis (dashed orange lines). The ulnar nerve provides native innervation to the flexor carpi ulnaris muscle (dashed yellow line) and gets mapped to the brachialis muscle for users, if their residual limb is long enough. Note that there is a line missing from Figure 1 that would be solid yellow leading from the ulnar nerve to the brachialis muscle; for persons without limb difference, we are unable to place a sensor on the brachialis muscle because it lies deep to the biceps brachii. However, this does not have a negative effect on the data: during model training, we would compose the input feature vector from the signals matching up to the five nerves. For persons without limb difference, these channels are marked with pink boxes in Figures 1 and 2; for users we simply replace the flexor carpi radialis, flexor carpi ulnaris, and extensor carpi radialis features with signals from the short head of the biceps brachii, brachialis, and lateral head of the triceps brachii, respectively. For each column in Figure 1, a solid-colored square marks that the muscle is a prime mover for the corresponding action along the y-axis. A hatched square denotes that the muscle is either a synergist or there is anticipated noise due to its proximity to the prime mover for the given action.

Data Collection Protocol

Three participants without limb difference, two males (26 years old, 193 cm, 104 kg, right-handed; 33 years old, 178 cm, 100 kg, left-handed) and one female (40 years old, 170 cm, 70 kg, right-handed), provided informed consent and were recruited for this pilot study (P1, P3, and P2 in Figure 2, respectively). We used the Delsys Trigno Wireless Biofeedback System with the Trigno Avanti sensors (Delsys) set to broadcast EMG signals at 1926 Hz and accelerometer data at 74 Hz. Eight sensors were placed on each arm in the middle of the muscle belly for each muscle in Figure 1 (x-axis); the solid-coloured actions in each column can be used to help find the correct muscle belly. The participants' dominant arm was then braced with the elbow bent at approximately 70°, forearm at mid-pronation, and wrist straight. This bracing position was chosen to lock the arm approximately in the middle of each joint's range of motion. This was to elicit isometric contractions to capture a higher amplitude from the signal for a longer duration, which we expect to be more similar to the type of muscle contractions a person with limb difference has. On the unbraced side, isotonic contractions are elicited as the participants moved actively through the range of motion, producing concentric contractions in the prime mover and synergist muscles.



(a) Unbraced arm (isotonic contractions)

(b) Braced arm (isometric contractions)

Figure 2: Consolidated muscle activation heatmap showing the results of our pilot study. In each column, activation is ranked with the highest number (normalized mV) denoting a given muscle as the prime mover for the corresponding action and lower numbers denoting lesser/minimal involvement in the action.

An interactive video played on a monitor in front of the participant to visually guide them through the data collection process. Participants follow a series of 11 actions (Figure 2, y-axis) in 13 limb positions to curate a dataset that covers the functional workspace of the human arm, including positions above the shoulder and behind the back. Three cross-body positions were also included but were found to be awkward to perform and their removal had minimal effect on the results. Once the participant was ready, a random limb position was presented on the monitor, and they were guided through a pre-ordered set of actions in that position. Each action was held for five seconds. Each participant carried out one training session guiding them through all 11 actions in one limb position before starting the full data collection process. After each limb position the participant was allowed to rest before continuing to the next limb position or redoing the last. To prepare the raw data for analysis, a bandpass filter from 20–450 Hz and a notch filter at 60 Hz was applied. The mean absolute value feature was then extracted using a sliding window of size 50 in increments of 10 samples. The participant data was aggregated into unbraced and braced groups to compare the difference bracing (i.e., isotonic vs. isometric) has on the muscle signals, and to account for differences in handedness. For clear visualization in Figure 2, each action-sensor pair were normalized by the greatest mean activation signal (mV) obtained for that sensor across all actions and limb positions.

RESULTS

The heatmaps shown in Figure 2 highlight the potential of our new data collection protocol to provide meaningful signals for each action across all limb positions. Figures 2a and 2b show the data from all three participants consolidated and normalized by sensor for the unbraced and braced arms, respectively. Each column provides a ranked order of activation strengths for the muscle, with the highest number reflecting the highest contractile strength for that action relative to all the other actions. The grey mini-maps contain the highest mean activation signal obtained for each sensor. Despite its normal overall activation pattern, the lateral head of the triceps brachii muscle value for P1 was an order of magnitude higher than all other mean activation signals. Further investigation suggests this may have been due to the participant activating this muscle to counteract the weight of the brace during elbow flexion in limb positions above the shoulder line. We focus our analysis on the five muscles marked with pink boxes in Figures 1 and 2 as these are the signals we would use for training a TMR prosthesis control model. In a ML model, the input would be the vector of EMG signals (e.g., the five signals from one row of the heatmap) and the output would be the action label (i.e., one of the y-axis labels).

Comparing Figure 2 with the anatomical expectations in Figure 1, a similar activation pattern emerges. Note that, as expected, the unbraced arm more closely matches the expected pattern as these predictions are based off anatomical muscle tables [12]. For the unbraced arm (Figure 2a), results reflect that the triceps brachii is the prime mover for elbow extension, the biceps brachii for elbow flexion, the flexor carpi radialis and flexor carpi ulnaris for wrist flexion, and the extensor carpi radialis for wrist extension. Interestingly, when compared with the isometric contractions elicited in the braced arm (Figure 2b) we see less distinct signals for each action as muscles close to the prime mover are also activated during the sustained contraction. This is shown in similar activation patterns of the pronator teres, flexor carpi radialis, and flexor carpi ulnaris during both pronation and wrist flexion. The biceps brachii also exhibits higher activation during supination than elbow flexion when braced, compared to unbraced. Both the unbraced and braced results reflect the effect of limb position on muscle contractions, as seen in the high activation signals for all forearm, wrist, and hand actions for the triceps and biceps brachii muscles. In fact, further investigation across individual limb positions show that EMG signals from the triceps and biceps brachii muscles begin to activate at a higher level across all actions as the participants raised their arms.

DISCUSSION AND CONCLUSION

Targeted muscle reinnervation (TMR) is a promising avenue for opening new and intuitive methods for myoelectric control. This work offers three key contributions to the field of advanced prosthetic control. Firstly, we introduce a bio-inspired protocol for collecting data in thirteen different limb positions targeted at training ML models for persons with transhumeral amputation that have undergone TMR surgery. We present results from a three-person pilot study using our proposed data collection protocol, highlighting its potential utility. Data from this limited sample mirrors what would be expected from anatomical predictions of which muscles should be active during each given action; this is most noticeable in the unbraced arm and provides validation for our choice of sensor placement. By analyzing muscle activation patterns for different upper limb actions, we can anticipate which actions ML models should be able to accurately predict for users. These actions are elbow flexion and extension, forearm supination and pronation, wrist flexion and extension, and radial and ulnar deviation. A model would have trouble predicting hand open and close accurately if included in this set of labels. Secondly, this study also touches on the limb position effect (c.f., Williams et al. [8]), which is reflected in the data and enables us to further analyze the effect of limb position on muscle contractions. Future work will include a more detailed analysis of this effect across all thirteen limb positions. Thirdly, our protocol captures the differences between isotonic (unbraced) and isometric (braced) muscle contractions, which will be of particular interest when comparing with data from users in future investigations. Looking ahead, we plan to streamline training processes by exploring ML-based transfer learning techniques as well as identifying the minimal number of limb positions and sensors needed during data collection to capture the full set of arm actions. In conclusion, this work presents a novel data collection protocol for TMR prosthesis control that uniquely reveals the interplay between limb position and muscle activation, while capturing the differences between isotonic and isometric contractions. This research sets the stage for training limb-position-aware prosthetic control models, offering the flexibility to use data from persons without amputations or a TMR user's non-amputated limb. Our approach has the potential to help streamline the development of a new generation of TMR-ready control solutions designed to improve the lives of persons with transhumeral amputations.

ACKNOWLEDGEMENTS

This work was supported by Amii, NSERC, Alberta Innovates, the Canada CIFAR AI Chairs Program, and the department of defense, Peer Reviewed Orthopaedic Research Program (PRORP) under Award no. HT9425-23-1-0398. This study was approved by the University of Alberta Research Ethics Board (Pro00077893). We thank Dylan Brenneis, Michael R. Dawson, Justin Francis, and Johannes Günther for their support and feedback. Special thanks to Shaylee Lorrain for graphical design assistance.

REFERENCES

[1] J. E. Cheesborough, L. H. Smith, T. A. Kuiken, and G. A. Dumanian, "Targeted muscle reinnervation and advanced prosthetic arms," *Seminars in Plastic Surgery*, vol. 29, no. 01, pp. 062–072, 2015.

[2] E. Scheme and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: state of the art and challenges for clinical use," *Journal of Rehabilitation Research & Development*, vol. 48, no. 6, 2011.

[3] F. Cordella, et al., "Literature review on needs of upper limb prosthesis users," *Frontiers in Neuroscience*, vol. 10, p. 209, 2016.

[4] T. A. Kuiken, et al., "Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms," *Jama*, vol. 301, no. 6, pp. 619–628, 2009.

[5] T. A. Kuiken, G. A. Dumanian, R. D. Lipschutz, L. A. Miller, and K. Stubblefield, "The use of targeted muscle reinnervation for improved myoelectric prosthesis control in a bilateral shoulder disarticulation amputee," *Prosthetics and Orthotics International*, vol. 28, no. 3, pp. 245–253, 2004.

[6] T. A. Kuiken, et al., "Targeted reinnervation for enhanced prosthetic arm function in a woman with a proximal amputation: a case study," *The Lancet*, vol. 369, no. 9559, pp. 371–380, 2007.

[7] L. J. Hargrove, L. A. Miller, K. Turner, and T. A. Kuiken, "Myoelectric pattern recognition outperforms direct control for transhumeral amputees with targeted muscle reinnervation: a randomized clinical trial," *Scientific Reports*, vol. 7, no. 1, p. 13840, 2017.

[8] H. E. Williams, et al., "Composite recurrent convolutional neural networks offer a position-aware prosthesis control alternative while balancing predictive accuracy with training burden," *2022 Int. Conf. on Rehabilitation Robotics (ICORR)*, Rotterdam, Netherlands, pp. 1-6, 2022.

[9] A. W. Shehata, H. E. Williams, J. S. Hebert and P. M. Pilarski, "Machine learning for the control of prosthetic arms: Using electromyographic signals for improved performance," *IEEE Signal Processing Magazine*, vol. 38, no. 4, pp. 46–53, 2021.

[10] H. Shinohara, H. Naora, R. Hashimoto, T. Hatta, and O. Tanaka, "Development of the innervation pattern in the upper limb of staged human embryos," *Acta Anatomica*, vol. 138, no. 3, pp. 265–269, 1990.

[11] H. H. Srebnik, "Innervation of upper limbs," *Concepts in Anatomy*, ch. 20, pp. 135–142, New York, NY: Springer, 1 ed., 2002.

[12] F. H. Netter, "Upper limb muscle tables," *Atlas of Human Anatomy*, ch. 6, pp. 6-1–6-4, Philadelphia, PA: Saunders/Elsevier, 6 ed., 2014.