Journal of Neural Engineering

PAPER

Use of regenerative peripheral nerve interfaces and intramuscular electrodes to improve prosthetic grasp selection: a case study

To cite this article: Christina Lee *et al* 2022 *J. Neural Eng.* **19** 066010

IOP Publishing J. Neural Eng. 19 (2022) 066010 https://doi.org/10.1088/1741-2552/ac9e1c

Journal of Neural Engineering

RECEIVED
17 May 2022

REVISED
26 September 2022

ACCEPTED FOR PUBLICATION
27 October 2022

PUBLISHED
14 November 2022

PAPER

Use of regenerative peripheral nerve interfaces and intramuscular electrodes to improve prosthetic grasp selection: a case study

Christina Lee[1], **Alex K Vaskov**[1], **Michael A Gonzalez**[2], **Philip P Vu**[3], **Alicia J Davis**[4], **Paul S Cederna**[1,3], **Cynthia A Chestek**[1,2] **and Deanna H Gates**[1,2,5,*]

[1] Department of Biomedical Engineering, University of Michigan, Ann Arbor, MI, United States of America
[2] Department of Robotics, University of Michigan, Ann Arbor, MI, United States of America
[3] Section of Plastic Surgery, University of Michigan, Ann Arbor, MI, United States of America
[4] Department of Physical Medicine and Rehabilitation, University of Michigan, Ann Arbor, MI, United States of America
[5] School of Kinesiology, University of Michigan, Ann Arbor, MI, United States of America
[*] Author to whom any correspondence should be addressed.

E-mail: gatesd@umich.edu

Keywords: upper limb loss, amputation, neural control, hand, myoelectric prosthesis

Supplementary material for this article is available online

Abstract

Objective. Advanced myoelectric hands enable users to select from multiple functional grasps. Current methods for controlling these hands are unintuitive and require frequent recalibration. This case study assessed the performance of tasks involving grasp selection, object interaction, and dynamic postural changes using intramuscular electrodes with regenerative peripheral nerve interfaces (RPNIs) and residual muscles. *Approach.* One female with unilateral transradial amputation participated in a series of experiments to compare the performance of grasp selection controllers with RPNIs and intramuscular control signals with controllers using surface electrodes. These experiments included a virtual grasp-matching task with and without a concurrent cognitive task and physical tasks with a prosthesis including standardized functional assessments and a functional assessment where the individual made a cup of coffee (‘Coffee Task’) that required grasp transitions. *Main results.* In the virtual environment, the participant was able to select between four functional grasps with higher accuracy using the RPNI controller (92.5%) compared to surface controllers (81.9%). With the concurrent cognitive task, performance of the virtual task was more consistent with RPNI controllers (reduced accuracy by 1.1%) compared to with surface controllers (4.8%). When RPNI signals were excluded from the controller with intramuscular electromyography (i.e. residual muscles only), grasp selection accuracy decreased by up to 24%. The participant completed the Coffee Task with 11.7% longer completion time with the surface controller than with the RPNI controller. She also completed the Coffee Task with 11 fewer transition errors out of a maximum of 25 total errors when using the RPNI controller compared to surface controller. *Significance.* The use of RPNI signals in concert with residual muscles and intramuscular electrodes can improve grasp selection accuracy in both virtual and physical environments. This approach yielded consistent performance without recalibration needs while reducing cognitive load associated with pattern recognition for myoelectric control (clinical trial registration number NCT03260400).

1. Introduction

The loss of an upper limb has a major impact on individuals’ quality of life and perceived function [1, 2]. With a myoelectric prosthesis, individuals can complete activities of daily living (ADLs), but are typically restricted to only a single motion of the hand or terminal device (open/close). This limitation results in low movement quality [3–5] and metabolic inefficiency [6] when completing various ADLs with a prosthesis. Moreover, prosthesis users must use alternative movement strategies that involve overreliance of their intact limb and the trunk [7, 8], leading to secondary health complications [9]. Advanced myoelectric prostheses are designed to improve existing prosthetic function by providing increased degrees-of-freedom (DoFs) of the terminal device. Unfortunately, these advanced devices remain difficult to control with low reliability of wrist motion and prosthetic grasp selection [10–12]. Unsurprisingly, prosthetic dissatisfaction rates remain high [13], suggesting further work is needed to improve function of upper limb prostheses.

Advanced myoelectric prostheses that provide additional movements of the terminal device require additional control signals beyond the standard pair of agonist-antagonist muscles. To switch between different grasps (e.g. pinch, point), prosthesis users can use additional control inputs such as muscle triggers, or gestures of the forearm or foot [10, 14, 15]. These methods require prosthesis users to pause during their movements and execute an unrelated task (i.e. double impulse of muscles, moving the arm quickly, moving the foot). Electromyography (EMG) pattern recognition may provide a more intuitive means for prosthetic grasp selection. With pattern recognition, machine learning is used to distinguish multiple movements from EMG signals acquired via an array of electrodes in the prosthetic socket [16–18]. Prosthesis users may calibrate the pattern recognition system using activation of EMG signals during either movements that correspond to the desired functional grasp or an alternative movement that outputs a stronger and more distinct muscle pattern. Current commercial systems, such as Sense [19] or Coapt [20], typically use surface EMG electrodes. Using surface electrodes requires users to frequently recalibrate due to inconsistent placement of the electrodes from donning and doffing the prosthesis or shifting of the prosthetic socket over the course of the day [11, 21–23]. As such, prosthesis users of pattern recognition systems have reported that the frequent need to recalibrate made the system tiring and difficult to use [11]. Low muscle specificity and cross-talk between electrodes also limit movement selection accuracy [21, 24, 25]. While currently available commercial systems for prostheses with multiple DoF report reliable activation of three to six distinct movements of the hand and wrist [10, 14], individuals who use these prostheses expressed greater cognitive demand during functional assessments compared to when using direct control [12]. Moreover, myoelectric prostheses with multiple DoF have not consistently improved functional scores [26, 27] or movement quality [4] in prosthesis users compared to using a prosthesis with a single DoF terminal device.

The use of implanted intramuscular EMG electrodes can address some of the challenges associated with using surface EMG for pattern recognition. Several studies have demonstrated the ability to acquire control signals with high muscle specificity, high signal-to-noise ratio (SNR), and reduced electrode cross-talk using intramuscular electrodes [21, 28–30]. Accordingly, the use of intramuscular EMG signals for hand and wrist movement classification has either maintained [22, 31] or improved [32–34] classification accuracy compared to the use of surface electrodes. However, these studies were performed in healthy individuals with full musculature. The substitution of surface EMG with intramuscular EMG alone may not necessarily improve the reliability of grasp selection, as this approach still limits the acquisition of control signals from the residual muscles only. Previous work in individuals with transradial amputation found that residual forearm muscles provide sufficient information to control wrist motion but not multiple hand grasps [25]. This highlights the importance of intrinsic muscles to achieve hand grasp selection with reliable accuracy. Unfortunately, intrinsic muscles of the hand that once provided fine digital dexterity are absent following amputation, which is why prosthetic grasp selection using only signals acquired from the residual musculature may be difficult.

To capture these absent control signals, researchers have attempted to measure efferent motor action potentials from the nerve, which were originally intended to control the missing musculature of the hand. Some previous work have achieved this by placing electrodes to record directly from the nerves, using devices such as multi-electrode arrays that record from the nerve fascicles and nerve cuffs placed around the neural compartments [35]. While this approach has the benefit of recording directly from the nerves with high specificity, the SNR of the nerve signals are smaller than muscle signals. Moreover, previous work have shown that implantation of electrodes directly in or around the nerve may cause tissue build-up and foreign body responses that may impact signal quality [36]. The longevity of such systems has been assessed on a scale of months [35, 37–39] to years [36, 40].

Alternatively, others have accomplished acquisition of intrinsic and extrinsic hand signals by measuring EMG activity from reinnervated muscle targets [41–43]. For example, partially denervated intact muscle are reinnervated during the targeted muscle reinnervation (TMR) surgery [43]. With a dense array of surface EMG electrodes, individuals with TMR could control multiple DoF [44, 45], including specific motions that were previously unintuitive and difficult to control [44]. A study of eight individuals with amputation following TMR surgery found that utilizing these signals improved functional outcomes after six to eight weeks of at-home prosthetic use [18]. However, the procedure requires denervation of intact muscles and may lack specificity in control signals due to innervating the same muscle target with multiple nerve fascicles. Recently, a preliminary study reported that using implantable EMG to record from residual muscles and TMR provided improved control signals earlier than acquiring signals using surface electrode arrays [46].

The construction of regenerative peripheral nerve interfaces (RPNIs) is another approach designed to enable stable acquisition of additional prosthetic control signals with high muscle specificity [29] to improve current myoelectric grasp selection. In this approach, a surgeon wraps a free muscle graft around individually separated nerve fascicles in the residual limb. After these grafts are revascularized and reinnervated, they serve as a bioamplifier for the signals that are transmitted down the peripheral nerve [42, 47, 48]. These signals are difficult to record with surface electrodes as the constructs are small (typically 3 × 1.5 × 0.5 cm grafts) and are typically placed in surrounding musculature of the residual limb to promote revascularization. However, control signals from RPNIs can be captured by implanting intramuscular electrodes. Previously, Vu *et al* demonstrated that intramuscular recording of RPNIs had consistently high SNR for over one year post-implantation in two individuals with amputation [29]. Using these control signals, participants controlled virtual finger movements with high accuracy, including thumb flexion and opposition, which were exclusively achieved using RPNI signals [29]. Additionally, the same participants had over 97% accuracy when selecting between four grasp postures and rest using RPNIs and residual muscle EMG [49]. Classification accuracy remained high for different static postures of the arm in one individual [49].

To expand on prior work, we conducted a case study to assess the use of RPNIs and intramuscular electrodes for tasks involving grasp selection, object interaction, and dynamic postural changes. In one experienced user of both virtual and physical myoelectric prostheses, we compared the performance of different pattern recognition classifiers with varying signal inputs (RPNIs and intramuscular residual muscles vs. surface residual muscles), calibration data (same-day vs. prior-day), and algorithm type (linear discriminant analysis (LDA) vs. hidden Markov model (HMM)). Within the use of intramuscular electrodes, we further evaluated the benefit of including RPNI signals to those of residual muscles on the classification of grasp and finger movements. We also quantified the cognitive demand associated with different controllers by having the participant complete a concurrent task while performing a virtual grasp selection task. Lastly, we quantified grasp selection performance during an ADL requiring multiple grasp selections while our participant controlled a myoelectric prosthesis. During this ADL, we also quantified segmental trunk angles to determine whether different controllers impact movement compensations typically seen in prosthesis users.

2. Methods

2.1. Participant and surgery details

The participant in our case study was labeled P4 [29] and P2 [49] in previous studies. Briefly, our participant was a 1.4 m tall 54 year old female who had a voluntary unilateral transradial amputation of her right hand to address her limited range of motion (ROM) and pain after an infection. During her amputation surgery, a surgeon constructed four RPNIs by suturing a 3 cm × 1.5 cm × 0.5 cm free muscle graft from her ipsilateral vastus lateralis to three free nerve endings: one on her median, one on her dorsal radial sensory, and two on her ulnar nerves. After surgery, her residual limb length was 10.45 cm from the cubital fold to distal end and she was fit with a body-powered prosthesis. While the participant self-reported wearing her prosthesis for approximately 48 h per week, she stated that she seldom actuated her terminal device to complete ADLs at home.

One year after amputation, the participant agreed to participate in this research study (clinical trial registration NCT03260400). As part of the study, a surgeon implanted eight bipolar electrodes (Synapse Biomedical, Oberlin, OH) into her residual muscles and RPNIs (figure 1). Originally developed for diaphragm control, these bipolar electrodes enable recording of EMG activity following implantation. One electrode was implanted in each of her two ulnar RPNIs and one in the median RPNI. Electrodes were also implanted in her flexor digitorum profundus indices (FDPIs), flexor pollicis longus, flexor carpi radialis, extensor pollicis longus, and extensor digitorum communis (EDC).

2.2. Myoelectric training with intramuscular signals

The participant had over one year of experience controlling a myoelectric prosthesis in the lab using intramuscularly acquired control signals of the five residual muscles and three RPNIs. During this time, the participant controlled a virtual prosthesis and completed functional tasks with an extra small i-Limb Quantum (Ossur, Reykjavik, Iceland) [29, 49]. We tracked the participant's training progress over a six month period (252–456 d following electrode implantation) by asking her to complete a series of standardized functional tests using two intramuscular control signals—FDPI and EDC. Specifically, she completed the abstract Southampton hand assessment procedure (SHAP) [50], box and blocks test (BBT) [51], and a modified version of BBT [52, 53]. Outcome measures for the SHAP and BBT were completion time and the number of blocks moved in a minute, respectively. Based on the established normative range of completion time [50], we calculated the index of functionality out of 100 for each functional

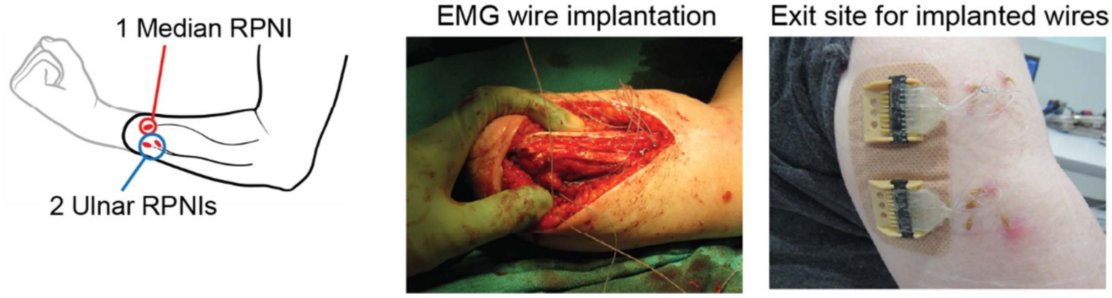

Figure 1. From left to right: illustration of placement of one median RPNI and two ulnar RPNIs relative to the level of the participant's amputation, surgical procedure of EMG electrode implantation, and the exit site of the chronically implanted EMG electrodes.

grasp involved during the SHAP. The modified BBT (MBBT) was further modified from previous studies [52, 53] such that the participant moved 16 blocks that were arranged in a raised 4-by-4 grid from the ipsilateral side to the contralateral grid (supplemental figure 1(B)). The outcome measure for the MBBT was completion time. The participant also completed BBT, MBBT, and the abstract SHAP using both her clinically prescribed body-powered prosthesis and her intact hand. We quantified the participant's average and best performance with a myoelectric prosthesis over the six month period and reported her best performance with her at-home body-powered prosthesis and her contralateral intact hand as reference.

The participant completed BBT over ten sessions, MBBT over nine sessions, and abstract SHAP over six sessions with the i-Limb. She completed BBT and MBBT over four sessions and the abstract SHAP in a single session using her body-powered prosthesis and her intact hand. Outcomes from different assessments over the six month period indicated that the participant was able to use the myoelectric hand as well as or better than her at-home body-powered device. The participant's performance with the i-Limb over time and reference performance with her at-home body-powered device and her contralateral left hand can be seen in supplementary figure 1.

2.3. Development of pattern recognition controllers

We developed a total of 27 pattern recognition controllers using the mean absolute value of eight pairs of bipolar electrodes as inputs (see supplemental material 1 for details) and predicted grasps as outputs. Across controllers, we varied signal acquisition method, available grasps, algorithm type, and calibration data. For acquisition methods, we used three approaches: gelled surface electrodes (Biopac Systems, Goleta, CA) ('Gelled'), commercially available socket-mounted dry surface electrodes (College Park Industries, Warren, MI) ('Dry'), and RPNIs and intramuscular electrodes ('RPNI'). For each of these acquisition methods, we built controllers to classify two (fist and finger abduction/open), three (add index finger point), or four (add pinch) distinct functional grasps and rest. We first built classifiers using LDA, which is commonly used to build pattern recognition controllers [15, 32, 33, 45, 54, 55], with Gelled, Dry, and RPNI signals. Following this initial comparison, we explored how algorithm type and calibration data influence grasp selection performance. Performance of classifiers with Gelled signals was not explored beyond the initial comparison, as the purpose of the experiment was to compare how intramuscular EMG and RPNIs compare to the commercial standard of surface based approach with dry electrodes. In addition to the LDA, we built classifiers using naïve bayes HMMs with Dry and RPNI signals, as prior work has demonstrated that using the HMM reduces transition errors and improves real-time grasp accuracy when using RPNI signals [49]. Finally, we used different calibration data to build each classifier (i.e. same-day, prior-day) to determine how robust Dry and RPNI classifiers were to calibration. Same-day controllers were built with calibration data collected at the beginning of each experimental session. Prior-day controllers used calibration data collected on a single day, up to 246 d prior for RPNI and up to 63 d prior for Dry signals.

2.4. Virtual grasp selection performance and cognitive load

The purpose of this experiment was to quantify grasp selection accuracy and associated cognitive demand of the different controllers in a virtual grasp selection task. In these experiments, the participant controlled a virtual prosthetic hand and was asked to match the grasp of a cue hand displayed on a computer screen [56] (figure 2(A)). The participant then repeated the task while concurrently completing the controlled oral word association test (COWAT). With COWAT, the participant listed as many words out loud as possible that started with a specific letter of the alphabet provided by the study team [57].

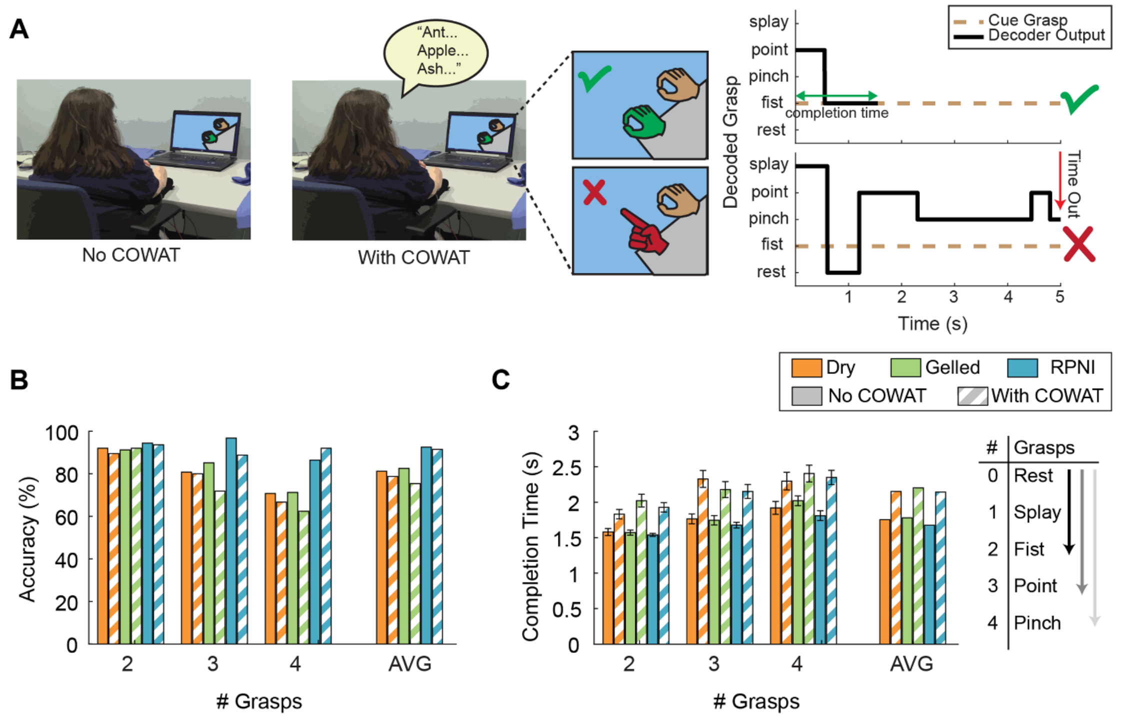

Figure 2. Illustration of the virtual grasp matching task. (A) The participant sat in front of a computer screen that displayed the cue grasp (shown in tan) and controlled the virtual hand with the controller's decoder output (shown in green for correct grasp and red for incorrect grasp). The participant was given five seconds per trial and was instructed to hold the accurate grasp for one second. If the correct grasp was not achieved after five seconds, the trial was marked as incorrect. The participant repeated the virtual task while simultaneously completing the controlled oral word association test (COWAT), during which she was asked to say as many words out loud as possible that started with a specific letter of the alphabet. (B) Grasp selection accuracy and (C) completion time of successful trials (mean $\pm$ standard error) over five sessions of 25 trials per session (total 125 trials) for Dry (orange), Gelled (green), and RPNI (blue) controllers with two, three, or four available grasps. The following conditions had missing trials due to computer error: Gelled with three grasps (121 trials), Gelled with three grasps and COWAT (121 trials), Dry with four grasps (123 trials), Dry with four grasps and COWAT (123 trials), Dry with two grasps and COWAT (123 trials). Virtual task accuracy and completion time of each controller with and without COWAT are illustrated with diagonal hatch patterns and solid bar graphs, respectively. Cognitive demand is reflected in a decreased accuracy and increased completion time with COWAT compared to task completion without COWAT.

We explored the effects of recalibration and the alternate pattern recognition algorithm (HMM) on grasp selection accuracy for a single experiment session (25 trials). We quantified grasp selection accuracy of RPNI and Dry controllers that classified two, three, and four functional grasps with varying algorithm type and calibration signal. We compared the performance of Dry and RPNI controllers built with either same-day calibration or prior-day calibration. For each calibration condition (same-day vs. prior-day), we also compared the performance of LDA and HMM when using either Dry or RPNI signals.

The participant completed a total of 25 trials of the virtual grasp selection task using each LDA controller ('Gelled'/'Dry'/'RPNI' × 'two-grasp'/'three-grasp'/'four-grasp') across five separate sessions. The participant always completed the four-grasp condition first, followed by three-grasp and two-grasp conditions. The order of testing for signal inputs varied based on availability of electrodes. The participant had months of training with pattern recognition prior to collection, so we did not anticipate learning would impact the results. Gelled and Dry controllers used calibration signals that were newly acquired each experimental session while RPNI controllers used the initial calibration data acquired up to 246 d prior. Data for RPNI controllers used the initial calibration data to reduce experiment time as the previous experiment suggested that there were very small differences between same-day and prior-day calibration. In each session, she repeated the same 25 trials with COWAT. For each trial, the participant had five seconds to match the target grasp and was instructed to hold the target grasp for one second. We quantified task accuracy as the percentage of successful trials out of total number of trials across all sessions. We also measured the average completion time of only the successful trials. Finally, we quantified the difference in grasp selection accuracy and average completion time as a measure of the cognitive load associated with each controller.

In order to determine the specific contributions of adding RPNIs to classification accuracy, we compared virtual grasp selection performance between a set of controllers built with intramuscular EMG signals from (a) residual muscles and RPNIs and (b) residual muscles only in a single experiment session.

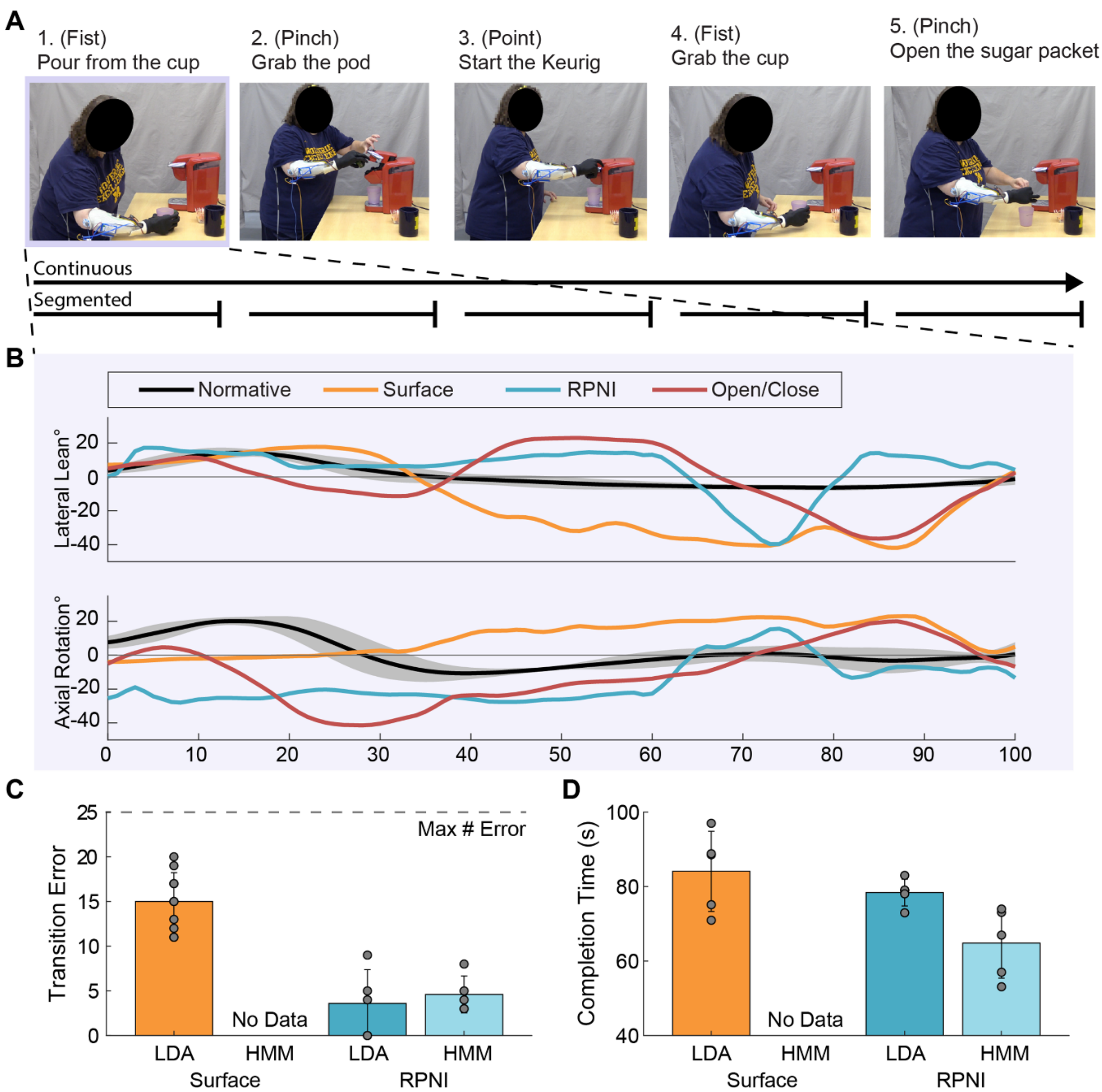

Figure 3. (A) Illustration of the Coffee Task, during which the participant simulated brewing a cup of coffee using five functional grasp transitions. The participant completed the task both continuously and in segments, with each grasp transition corresponding to a segment. (B) Representative triaxial trunk segmental angle trajectory during the first segment ('Pour from the cup') of the continuous Coffee Task using two-grasp (open/close; red), RPNI (blue), and Dry (orange) controllers. Positive angles represent lateral lean towards the prosthesis (or the right) and axial rotation away from the prosthesis (or counter-clockwise). The participant selected between four grasps with the RPNI and surface (Dry) controllers. The mean (black solid line) and standard deviation (grey shaded area) of normative joint trajectory of a non-amputee during the Coffee Task is plotted for reference. The participant employed greater range of motion (ROM) of the trunk using all controllers compared to the normative trajectory. (C) Average number of transition errors quantified during the segmented task and (D) average completion time quantified during the continuous task using surface LDA, RPNI LDA, RPNI HMM controllers. Error bars represent the standard deviation across trials while individual points represent data from each trial.

All controllers' calibration data were collected on the day of the experiment. The participant first completed the grasp selection task between up to four grasps and rest. She also completed the task with both functional grasps and individual finger movements to a maximum of eight classes—fist, finger abduction, thumb opposition, thumb flexion, index finger flex/extension, and middle-ring-small finger flex/extension. We subsequently decreased the number of available classes to six (remove index finger extension and middle-ring-small extension) and four (remove thumb opposition and flexion). The participant then repeated the set of experiments while simultaneously completing the COWAT.

2.5. Grasp selection during the coffee task

The purpose of this experiment was to quantify how well the participant can use different pattern recognition controllers to complete a functional representative activity of daily living. Specifically, we developed a 'Coffee Task' assessment to quantify how well the participant could transition between grasps when wearing a physical prosthesis to complete an activity of daily living (figure 3(A)). This is distinct from other functional outcomes where the individual uses a different grasp for different parts of the assessment (i.e. SHAP), but does not transition from one grasp to another during any measured portion of the assessment. Our Coffee Task required five grasp transitions (Refer to supplementary video 1 for the illustration of the task) and was completed in the following sequence: (a) a fist grasp to grasp the coffee cup to pour water (simulated with two beads) into the water reservoir of a Keurig mini (Reading, MA), (b) a pinch grasp to pick up the coffee pod and place into the pod holder, (c) a point grasp to start the Keurig, (d) a fist grasp to move the coffee cup from the coffee maker to the table, and (e) a pinch grasp in combination with the contralateral limb to open a sugar packet and pour the sugar into the cup. The participant was able to practice the Coffee Task with each controller for two sessions prior to data collection.

The participant completed a continuous Coffee Task five times with the Dry LDA, RPNI LDA, and RPNI HMM controller with three i-Limb grasps (fist/hand close, two-finger pinch, and point) and hand open (controller trained as finger abduction), each with proportional open-close commands [58, 59]. The participant did not complete the Coffee Task with any Gelled controllers, as we could not fabricate a prosthetic socket to accommodate gelled surface electrodes. In this version of the task, she was often able to continue and complete the task even when an incorrect grasp was used for a particular segment. To better quantify grasp errors, we also asked her to complete a segmented version of the task where each grasp transition signaling the next phase of the task sequence was performed as a separate segment. The participant was allowed five attempts per segment to accomplish the accurate grasp and repeated the segmented task five times with the RPNI controllers. The participant completed the segmented task ten times over two sessions with the Dry controller to account for the greater variability in performance seen. During the continuous Coffee Task, we calculated the average completion time across all five trials for each controller. During the segmented Coffee Task, we quantified both the non-transition errors (i.e. dropping of the objects, hand 'flutter' within an accurate grasp) and grasp transition errors with a maximum of 25 total errors per trial.

People with upper limb loss frequently use trunk motion to help them properly position their prosthesis to interact with an object [7, 8]. Here, we characterized trunk segmental angles during the Coffee Task with different pattern recognition controllers. Visual inspection indicated that our participant employed the greatest amount of compensatory movement strategies when she was simulating pouring a cup of water into the coffee maker reservoir. During this segment of the continuous Coffee Task, we tracked the position of four reflective markers placed on the trunk (sternal notch, xiphoid process, seventh cervical vertebra, and eighth thoracic vertebra) at 120 Hz using a 12-camera motion capture system (Motion Analysis, Santa Rosa, CA). Marker position data were filtered using a fourth-order lowpass Butterworth filter with a cutoff frequency of 6 Hz in Visual 3D (C-Motion, Germantown, MA). Trunk motion was defined relative to the global reference frame according to [60]. Trunk segmental angles were time normalized from 0% to 100% of task completion. We quantified the ROM of the trunk segmental angle as the participant completed the task with two multi-grasp controllers (Dry LDA, RPNI LDA).

3. Results

3.1. Virtual grasp selection performance and cognitive load

In a single session (25 trials), we explored the effects of varying calibration condition (prior-day vs. same-day) and pattern recognition algorithm type (LDA vs. HMM) on grasp selection accuracy of Dry and RPNI controllers. During this exploratory session, controllers built using RPNI signals had consistently high performance (100% accuracy) compared to those using dry surface signals (69.0% accuracy), regardless of calibration day (same-day vs. prior-day) or pattern recognition algorithm type (LDA vs. HMM). With prior-day calibration, grasp selection accuracy of the Dry controllers with both LDA and HMM decreased to 56% or below with the exception of the two-grasp HMM controller (100%).

We then assessed grasp selection performance and associated cognitive demand of each control approach by having the participant complete variations of a virtual grasp selection task with and without a concurrent cognitive task. This task was repeated with controllers using two to four available grasps with either dry surface (Dry), gelled surface (Gelled), or intramuscular control signals with RPNIs (RPNI). For all trials, across all sessions of two, three, and four grasp controllers, the RPNI LDA controller had the highest average accuracy of 92.5%, followed by Gelled (82.5%) and Dry LDA (81.2%) surface controllers (figure 2(B)). Within the two-grasp controllers (fist and rest), all controllers had an accuracy above 90%. For all signal inputs, grasp selection accuracy decreased as the number of available grasps increased. Differences between the controllers with different signal inputs were more pronounced as more grasps were included, with the RPNI LDA controller having the smallest reduction in performance.

Across two, three, and four available grasps, the participant completed successful trials the fastest using the RPNI LDA controller (figure 2(C)). Across all sessions, the average completion times for Dry, Gelled, and RPNI LDA controllers were 1.76, 1.78, and 1.68 s respectively across all sessions. For all controllers, completion time increased as the number of grasps increased.

When the participant completed the concurrent cognitive task, her completion times increased by an average of 429 ms with the maximum possible completion time of 5 s across all controllers. The participant's grasp selection accuracy decreased by

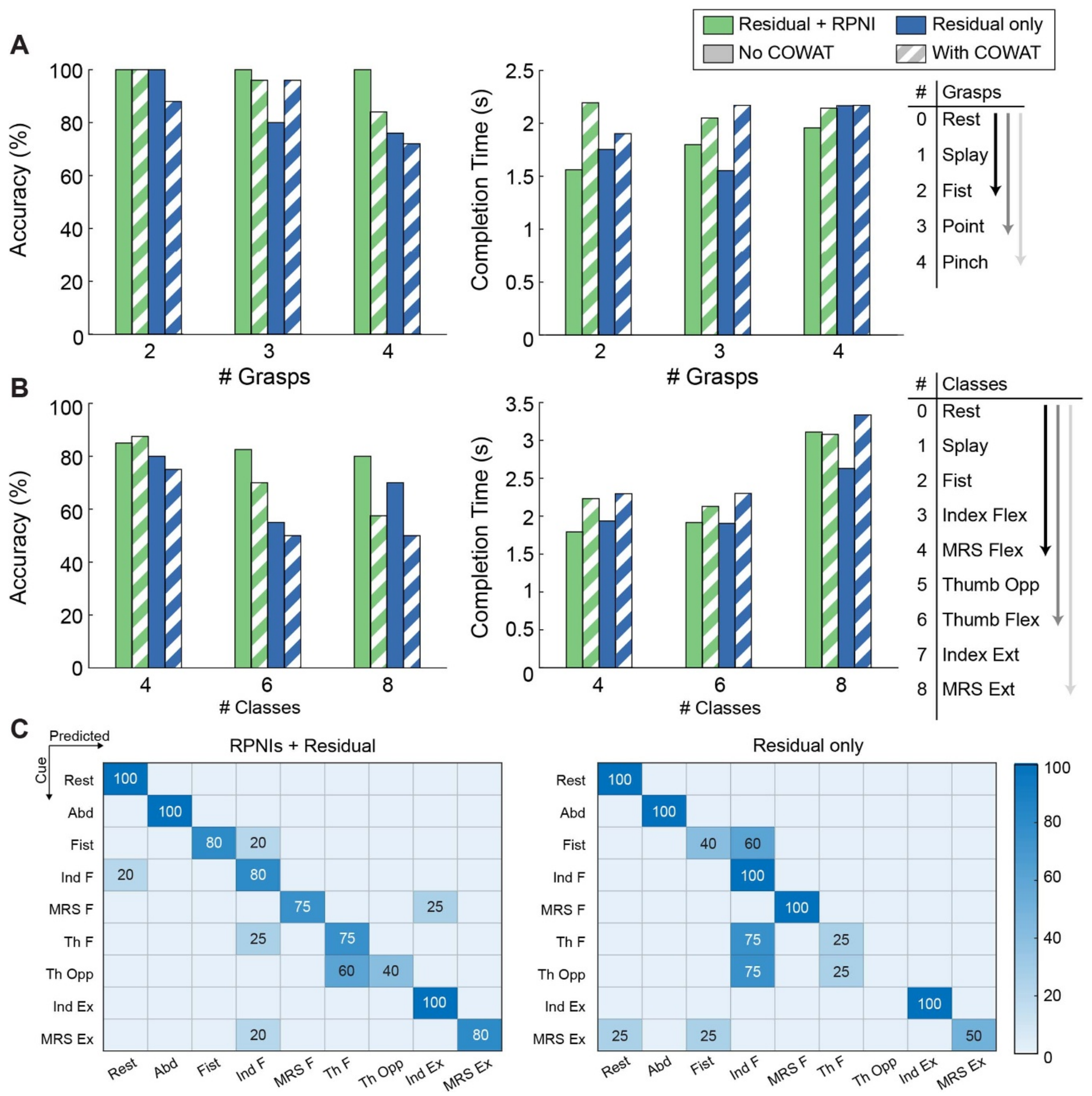

Figure 4. Virtual task selection accuracy and completion time of successful trials over a single session of 40 trials for the controller built with residual muscles and RPNIs (green) and with residual muscles only (blue) with (A) two, three, or four available grasps and (B) four, six, or eight available classes (grasps and thumb, index, and middle-ring-small (MRS) finger movements). Virtual task accuracy and completion time of each controller with and without COWAT are illustrated with diagonal hatch patterns and solid bar graphs, respectively. (C) Confusion matrix of eight available classes—Rest, Finger abduction (Abd), Fist, Index finger flexion (Ind F), MRS finger flexion (MRS F), Thumb finger flexion (Th F), Thumb finger opposition (Th Opp), Index finger extension (Ind E), MRS finger extension (MRS E)—of controllers with RPNIs and residual muscles (left) and with residual muscles only (right). Grasp selection percentage is normalized to the incidence of each cue class and reported as percentages.

2.4%, 7.1% and 1.1%, when performing the concurrent cognitive task using the Dry, Gelled and RPNI LDA controllers, respectively.

We also explored the benefits of including RPNIs as control signal inputs specifically by building controllers that did not include these signals (i.e. residual muscles only) and comparing their performance against controllers with residual muscles and RPNIs. When selecting between two grasps (finger abduction and fist), both controllers with and without RPNIs had an accuracy of 100% (figure 4(A)). When the number of available grasps increased, controllers with only residual muscle had degraded performance (80% at three grasps and 76% at four grasps), while those including RPNIs maintained 100% accuracy. There were no consistent trend for changes in completion time between different signal inputs.

There was a consistent benefit to including RPNIs in the classification of both grasp and finger movements (average improvement of 14.2%), with the greatest improvements for the larger number of classes including thumb movements (figure 4(B)). Notably, with all eight classes, the controllers could achieve thumb flexion with 75% and 25% accuracy with and without RPNIs, respectively. There were no consistent difference in completion time between controllers.

With the concurrent cognitive task, the participant completed the task with reduced selection accuracy and increased completion time for all controllers. There were no consistent trends in outcomes between controllers with and without RPNIs.

3.2. Grasp selection during the coffee task

In this experiment, we evaluated whether controller inputs (surface/RPNI) affected grasp selection errors and completion time of a physical coffee making task that required three functional grasps and active open. We also explored how the type of pattern recognition algorithm (LDA vs. HMM) impacted grasp selection using RPNIs during this task. The participant did not complete the Coffee Task with the Dry HMM controller for four grasps, as she was not able to reliably transition to closing the fist and pinch grasps using this controller. Therefore, the participant completed the Coffee Task using only the Dry LDA, RPNI LDA, and RPNI HMM controllers with three functional grasps. Across five trials of the continuous Coffee Task, the RPNI HMM controller had the shortest average completion time of 64.8 s compared to the RPNI LDA controller (78.4 s) and the Dry LDA controller (84.1 s) (figure 3(D)). For reference, three healthy individuals without limb loss (two males, one female; age 33 $\pm$ 6) completed the Coffee Task with an average completion time of 13.71 s across five trials.

Using the Dry LDA controller, the participant completed the segmented Coffee Task with an average of 15 total errors out of a maximum of 25 possible errors, of which 14 were transition errors (figure 3(C)). In contrast, the RPNI LDA controller had an average of four errors with zero non-transition error. With the RPNI HMM, the participant completed the task with an average of five errors with zero non-transition error. For the RPNI LDA controller, 11 out of 17 (64.7%) total transition errors over all five trials consisted of misclassifications of pinch grasp when the participant attempted a fist grasp. For the Dry LDA controller, 45 out of 141 (31.9%) total transition errors over all trials consisted of misclassification of fist grasp when the participant attempted a pinch grasp.

We assessed trunk compensations during the pouring segment of the continuous Coffee Task. Using the Dry LDA controller, the participant reduced her average ROM by 9° lateral lean and 16° axial rotation compared to when using the RPNI surface controller. For both surface and RPNI controllers, the participant had greater trunk ROM than what was used by a healthy non-amputee completing this task (21° lateral lean, 31° axial rotation, 9° flexion).

4. Discussion

In this study, we demonstrated that the use of RPNIs and intramuscular electrodes can improve functional performance during the control of multi-articulating hands without the need for recalibration. Moreover, the inclusion of RPNIs as signal inputs in pattern recognition systems improved class selection accuracy in both grasp-only classifiers and classifiers with grasps and individual finger movements. In both virtual and physical environments, our participant consistently had higher grasp selection accuracies and faster completion times when using controllers built from RPNIs and intramuscular EMG compared to those using surface EMG. Our participant's grasp selection performance was also more consistent when using controllers built from RPNIs and intramuscular EMG to those built from surface EMG while simultaneously completing a cognitive task. Therefore, the approach of using RPNIs and acquiring control signals intramuscularly may be less cognitively demanding than conventional commercial control approaches. In addition, we explored different controller configurations with varying calibration day (prior-day vs. same-day) and machine learning algorithm (LDA vs. HMM). Controllers built from RPNIs and intramuscular EMG had consistently high selection accuracy and were less affected by varying machine learning algorithms and calibration data than those from surface EMG.

In this study, we expanded on prior work by demonstrating that the inclusion of RPNI signals can improve classification accuracy, for both grasp-only classifiers and classifiers with grasps and individual finger control. In particular, inclusion of RPNI signals provided large improvements in the classification of individual finger movements, including those of the thumb. In fact, thumb movement classification was not achievable without RPNI signals (accuracy 0%–25% with residual muscles only). This improvement indicates that RPNI signals contain important information for intrinsic hand muscles. Similarly, previous studies have demonstrated that RPNIs provide reliable multi-DoF thumb control with a regression algorithm [29] and can be used for classification of finger abduction/adduction in a virtual environment [29, 49]. However, due to the lack of commercially available hardware that enables movements of individual fingers, it remains unclear how well RPNIs can be used to control individual fingers in a physical environment.

The need to frequently recalibrate is identified as one of the major drawbacks of using surface pattern recognition systems. Previous work have acknowledged that recalibration of control signals may be needed as the system performance may deteriorate over time as electrode positions shift and users fatigue [61]. Understanding that recalibration is a major feature of currently available pattern recognition systems, training guidelines for pattern recognition system users include helping users recognize when recalibration is needed, which may be necessary multiple times a day [23]. One prior take-home study of a pattern recognition system with surface EMG reported that several users expressed frustration with the decrease in responsiveness of their prostheses, prompting them to frequently recalibrate. Additionally, users reported that calibration may or may not be successful in their initial attempt [11]. As such, prior studies have explored intramuscular EMG as an alternative to commercial surface EMG and reported that their approach can improve muscle specificity and reduce calibration needs while maintaining consistently high decode accuracy [21, 28, 29]. Similarly, our results demonstrate that using intramuscular signals eliminates recalibration needs for more than nine months, which is longer than the period of observation reported in previous studies. Using prior-day calibration, the Dry LDA controller accuracy decreased substantially from 80% to 20% during the virtual grasp selection task with four grasps. In contrast, the RPNI controllers that were built from signals acquired with intramuscular electrodes were equally accurate between prior-day and same-day calibration condition. This is particularly notable, since prior-day calibration signals were collected once and our participant used the identical controller for up to 246 d following. Thus, the use of intramuscular electrodes for grasp selection pattern recognition can eliminate recalibration needs for at least nine months. We expect that removing the need for recalibration through the use of RPNIs to achieve myoelectric pattern recognition would reduce frustration and promote more successful integration of prostheses in users' daily lives.

Grasp selection performance observed in virtual environments may not translate to performance expected in real-world environment. While our participant completed the virtual grasp selection task with an average of 95.6% accuracy with her RPNI LDA controller, she made an average of 4 errors out of 25 maximum possible errors during the segmented Coffee Task. Nevertheless, our participant completed the Coffee Task with greater accuracy and shorter completion time when she was using RPNI signals compared to when using surface EMG signals. There are several challenges that exist in real world environments that do not apply to virtual tasks that may explain the sources of these errors. In a virtual environment, multiple grasps can be rapidly predicted and actuated by the controller. In other words, the 'flutter' between grasps can be quickly corrected without compromising selection accuracy. However, the physical prosthesis may flutter within a correct grasp (non-transition error) or between a correct and an incorrect grasp (transition error) with additional hardware response times to consider during these selections. Even without any fluttering, the hardware interface delayed transition times between grasps. This could add frustration, especially when an incorrect grasp is selected and a correction must be made. The added weight of the prosthesis in a physical environment also likely shifted muscle activation patterns of our participant. Vaskov *et al* suggested that the RPNI controller accuracy in virtual tasks is consistent across different static arm postures with a donned prosthesis [49]. However, dynamic movements of the prosthetic limb required during the Coffee Task may introduce movement artifacts, especially with surface EMG signals. These artifacts can result in muscle activation patterns that are no longer reflective of the original patterns used to build the controllers, leading to low grasp selection accuracy. Furthermore, the involvement of object interactions required our participant to learn how to optimize hand orientation given the object and the required grasp. This is particularly challenging given the lack of sensory feedback offered by the prosthesis used in this study and the majority of the prosthesis available today. As such, our participant made several non-transition errors such as dropping the object.

How the availability of multiple functional grasps impacts prosthesis users' movement patterns and compensatory strategies has not been sufficiently explored. In this case study, we also assessed the differences in movement strategy during the Coffee Task completed with multi-grasp controllers (with surface or RPNI signals) and a single DoF (open/close) RPNI controller. Visually, we noted that the participant made significant compensatory movements with her trunk to successfully complete the task. In particular, our participant leaned her trunk toward her intact limb and supported her weight with the intact hand as she poured the beads from the cup into the coffee machine reservoir (refer to supplementary video 1 for the illustration of this movement). She also shifted her body position around the perimeter of the table to ease the manipulation of the objects during various parts of the task. It is possible that the participant's physical limitations prevented her from using any other movement strategy than those that involved excessive trunk ROM. Due to the repeated surgical procedures to address the initial complication that eventually led to her amputation, the participant experienced limited ROM in shoulder elevation and elbow flexion. It is also possible that our participant was more reliant on her trunk ROM due to the lack of active wrist control. Previous work suggested that wrist dexterity is more essential than finger dexterity to reduce prosthetic movement compensations [62]. Therefore, the addition of a motorized wrist unit, along with functional grasps, may be beneficial in employing movement strategies that are less prone to joint health complications [9].

There are several limitations to consider when interpreting the results from this study. Our case study only involved one individual due to the relative invasiveness of the procedure, the necessity of extended and frequent laboratory visits, and COVID testing restrictions. As such, results in this study may not generalize to the broader population with amputation who have different amputation levels, residual muscle control, and prosthetic experience. Also, our participant used a body-powered prosthesis at home, so her myoelectric control experience was confined within the time spent in the lab. The participant gained numerous hours of myoelectric control experience over the three years of study enrollment. While she learned how to control a physical myoelectric prosthesis over the six month training period with various functional assessments, she did not receive any physical or occupational therapy. This lack of systematic clinical training may have influenced her overall myoelectric control proficiency. It is possible that learning influenced her results with each signal input type as her experience with each varied. However, we believe this is unlikely as she had over a year of experience controlling a virtual prosthesis with pattern recognition. While this was largely done with intramuscular signals, the principle of pattern recognition was consistent across different signal types. Lastly, we developed a novel functional task to quantify controller performance in a physical environment, as there are no existing validated assessment that quantify prosthetic grasp transitions. As such, it is difficult to compare this participant's performance to other prosthesis users or individuals using different grasp selection controllers. Nevertheless, we were able to make within-participant comparisons between different myoelectric controllers.

In conclusion, this case study demonstrated that the combined use of RPNIs and intramuscular EMG have the potential to improve myoelectric grasp selection, without recalibration, for up to nine months. Our participant completed both virtual and physical tasks with improved accuracy and faster completion time with RPNIs and intramuscular EMG compared to with surface EMG. Our participant's grasp selection performance was also more consistent with a concurrent cognitive task with RPNIs. Future work will focus on combining multi-grasp control with active wrist motion and include take-home studies to better characterize the potential of using RPNIs and intramuscular EMG in real-world settings.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

The authors have confirmed that any identifiable participants in this study have given their consent for publication.

Acknowledgments

The authors would like to thank Kelsey Ebbs for assisting with data collection. This work was supported by the National Institutes of Health under Award Number R01NS105132 to C A C. The opinions expressed in this article are the authors' own and do not reflect the view of the National Institutes of Health.

Statements and declarations

The University of Michigan holds a patent related to this work, Publication Number US20190262145A1: system for amplifying signals from individual nerve fascicles. The authors have no other conflicts of interest to declare.

This study was approved by the University of Michigan's Medical School IRB (IRB-MED) under Number HUM00124839. The clinical trial registration number associated with this study is NCT03260400. This research was conducted in accordance with the principles embodied in the Declaration of Helsinki and in accordance with local statutory requirements. All participants provided their written informed consent to participate in the study. The participant also consented to the use of their images in research publication.

ORCID iDs

Christina Lee https://orcid.org/0000-0003-3507-6147
Alex K Vaskov https://orcid.org/0000-0002-2336-9877
Cynthia A Chestek https://orcid.org/0000-0002-9671-7051
Deanna H Gates https://orcid.org/0000-0002-6086-0913

References

[1] Beasley R W 1981 General considerations in managing upper limb amputations *Orthop. Clin. North Am.* **12** 743–9
[2] Jang C H, Yang H S, Yang H E, Lee S Y, Kwon J W, Yun B D, Choi J Y, Kim S N and Jeong H W 2011 A survey on activities of daily living and occupations of upper extremity amputees *Ann. Rehabil. Med.* **35** 907–21
[3] Engdahl S M and Gates D H 2021 Differences in quality of movements made with body-powered and myoelectric prostheses during activities of daily living *Clin. Biomech.* **84** 105311
[4] Cowley J, Resnik L, Wilken J, Smurr Walters L and Gates D 2017 Movement quality of conventional prostheses and the DEKA arm during everyday tasks *Prosthet. Orthot. Int.* **41** 33–40
[5] Doeringer J A and Hogan N 1995 Performance of above elbow body-powered prosthesis in visually guided unconstrained motion tasks *IEEE Trans. Biomed. Eng.* **42** 621–31
[6] Nishii J and Taniai Y 2009 Evaluation of trajectory planning models for arm-reaching movements based on energy cost *Neural Comput.* **21** 2634–47
[7] Major M J, Stine R L, Heckathorne C W, Fatone S and Gard S A 2014 Comparison of range-of-motion and variability in upper body movements between transradial prosthesis users and able-bodied controls when executing goal-oriented tasks *J. Neuroeng. Rehabil.* **11** 1–10
[8] Carey S L, Jason Highsmith M, Maitland M E and Dubey R V 2008 Compensatory movements of transradial prosthesis users during common tasks *Clin. Biomech.* **23** 1128–35
[9] Jones L E and Davidson J H 1999 Save that arm: a study of problems in the remaining arm of unilateral upper limb amputees *Prosthet. Orthot. Int.* **23** 55–58

[10] Atzori M and Muller H 2015 Control capabilities of myoelectric robotic prostheses by hand amputees: a scientific research and market overview *Front. Syst. Neurosci.* **9** 162
[11] Resnik L J, Acluche F and Lieberman Klinger S 2018 User experience of controlling the DEKA arm with EMG pattern recognition *PLoS One* **13** e0203987
[12] Resnik L, Huang H, Winslow A, Crouch D L, Zhang F and Wolk N 2018 Evaluation of EMG pattern recognition for upper limb prosthesis control: a case study in comparison with direct myoelectric control *J. Neuroeng. Rehabil.* **15** 23
[13] Smail L C *et al* 2020 Comfort and function remain key factors in upper limb prosthetic abandonment: findings of a scoping review *Disabil. Rehabil.: Assist. Technol.* **16** 1–10
[14] Jiang N and Farina D 2014 Myoelectric control of upper limb prosthesis: current status, challenges and recent advances *Front. Neuroeng.* **7** 7–9
[15] Parajuli N *et al* 2019 Real-time EMG based pattern recognition control for hand prostheses: a review on existing methods, challenges and future implementation *Sensors* **19** 4596
[16] Cummins F *et al* 2017 Machine learning to improve pattern recognition control of upper-limb myoelectric prosthesis *Proc. Myoelectric Controls Symp.* (Canada: University of New Brunswick Fredericton)
[17] Simon A M *et al* 2019 Pattern recognition and direct control home use of a multi-articulating hand prosthesis *IEEE Int. Conf. on Rehabilitation Robotics* pp 386–91
[18] Hargrove L J, Miller L A, Turner K and Kuiken T A 2017 Myoelectric pattern recognition outperforms direct control for transhumeral amputees with targeted muscle reinnervation: a randomized clinical trial *Sci. Rep.* **7** 13840
[19] Infinite Biomedical Technologies 2022 *Sense* (available at: www.i-biomed.com/sense.html)
[20] Coapt 2022 (available at: https://coaptengineering.com/)
[21] Dewald H A, Lukyanenko P, Lambrecht J M, Anderson J R, Tyler D J, Kirsch R F and Williams M R 2019 Stable, three degree-of-freedom myoelectric prosthetic control via chronic bipolar intramuscular electrodes: a case study *J. Neuroeng. Rehabil.* **16** 147
[22] Kamavuako E N, Rosenvang J C, Horup R, Jensen W, Farina D and Englehart K B 2013 Surface versus untargeted intramuscular EMG based classification of simultaneous and dynamically changing movements *IEEE Trans. Neural. Syst. Rehabil. Eng.* **21** 992–8
[23] Simon A M, Lock B A and Stubblefield K A 2012 Patient training for functional use of pattern recognition-controlled prostheses *J. Prosthet. Orthot.* **24** 56–64
[24] Farina D, Jiang N, Rehbaum H, Holobar A, Graimann B, Dietl H and Aszmann O C 2014 The extraction of neural information from the surface EMG for the control of upper-limb prostheses: emerging avenues and challenges *IEEE Trans. Neural Syst. Rehabil. Eng.* **22** 797–809
[25] Li G, Schultz A E and Kuiken T A 2010 Quantifying pattern recognition-based myoelectric control of multifunctional transradial prostheses *IEEE Trans. Neural Syst. Rehabil. Eng.* **18** 185–92
[26] Van Der Niet O, Reinders-Messelink H A, Bongers R M, Bouwsema H and Van Der Sluis C K 2010 The i-LIMB hand and the DMC plus hand compared: a case report *Prosthet. Orthot. Int.* **34** 216–20
[27] Franzke A W, Kristoffersen M B, Bongers R M, Murgia A, Pobatschnig B, Unglaube F and van der Sluis C K 2019 Users' and therapists' perceptions of myoelectric multi-function upper limb prostheses with conventional and pattern recognition control *PLoS One* **14** e0220899
[28] Cipriani C, Segil J L, Birdwell J A and Weir R F F 2014 Dexterous control of a prosthetic hand using fine-wire intramuscular electrodes in targeted extrinsic muscles *IEEE Trans. Neural Syst. Rehabil. Eng.* **22** 828–36
[29] Vu P P *et al* 2020 A regenerative peripheral nerve interface allows real-time control of an artificial hand in upper limb amputees *Sci. Transl. Med.* **12** 1–11
[30] Weir R F, Troyk P R, DeMichele G A, Kerns D A, Schorsch J F and Maas H 2009 Implantable myoelectric sensors (IMESs) for intramuscular electromyogram recording *IEEE Trans. Biomed. Eng.* **56** 159–71
[31] Jochumsen M, Waris A and Kamavuako E N 2018 The effect of arm position on classification of hand gestures with intramuscular EMG *Biomed. Signal Process. Control* **43** 1–8
[32] Farrell T and Weir R 2005 Pilot comparison of surface vs. implanted EMG for multifunctional prosthesis control *Proc. 2005 IEEE 9th Int. Conf. on Rehabilitation Robotics* pp 277–80
[33] Smith L H and Hargrove L J 2013 Comparison of surface and intramuscular EMG pattern recognition for simultaneous wrist/hand motion classification *Annual Int. Conf. IEEE Engineering in Medicine and Biology Society* pp 4223–6
[34] Kamavuako E N, Scheme E J and Englehart K B 2014 Combined surface and intramuscular EMG for improved real-time myoelectric control performance *Biomed. Signal Process. Control* **10** 102–7
[35] Branner A, Stein R B, Fernandez E, Aoyagi Y and Normann R A 2004 Long-term stimulation and recording with a penetrating microelectrode array in cat sciatic nerve *IEEE Trans. Biomed. Eng.* **51** 146–57
[36] Christensen M B, Pearce S M, Ledbetter N M, Warren D J, Clark G A and Tresco P A 2014 The foreign body response to the Utah Slant Electrode Array in the cat sciatic nerve *Acta Biomater.* **10** 4650–60
[37] Davis T S, Wark H A C, Hutchinson D T, Warren D J, O'Neill K, Scheinblum T, Clark G A, Normann R A and Greger B 2016 Restoring motor control and sensory feedback in people with upper extremity amputations using arrays of 96 microelectrodes implanted in the median and ulnar nerves *J. Neural Eng.* **13** 036001
[38] Rijnbeek E H, Eleveld N and Olthuis W 2018 Update on peripheral nerve electrodes for closed-loop neuroprosthetics *Front. Neurosci.* **12** 350
[39] Warren D J, Kellis S, Nieveen J G, Wendelken S M, Dantas H, Davis T S, Hutchinson D T, Normann R A, Clark G A and Mathews V J 2016 Recording and decoding for neural prostheses *Proc. IEEE* **104** 374–91
[40] Simeral J D, Kim S-P, Black M J, Donoghue J P and Hochberg L R 2011 Neural control of cursor trajectory and click by a human with tetraplegia 1000 days after implant of an intracortical microelectrode array *J. Neural Eng.* **8** 025027
[41] Cheesborough J E, Smith L, Kuiken T and Dumanian G 2015 Targeted muscle reinnervation and advanced prosthetic arms *Semin. Plast. Surg.* **29** 62–72
[42] Urbanchek M G, Kung T A, Frost C M, Martin D C, Larkin L M, Wollstein A and Cederna P S 2016 Development of a regenerative peripheral nerve interface for control of a neuroprosthetic limb *Biomed. Res. Int.* **2016** 5726730
[43] Kuiken T A 2003 Consideration of nerve-muscle grafts to improve the control of artificial arms *Technol. Disabil.* **15** 105–11
[44] Zhou P, Lowery M M, Englehart K B, Huang H, Li G, Hargrove L, Dewald J P A and Kuiken T A 2007 Decoding a new neural machine interface for control of artificial limbs *J. Neurophysiol.* **98** 2974–82
[45] Kuiken T A *et al* 2009 Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms *JAMA* **301** 619–28
[46] Mastinu E *et al* 2018 Myoelectric signals and pattern recognition from implanted electrodes in two TMR subjects with an osseointegrated communication interface *Annual Int. Conf. IEEE Engineering in Medicine and Biology Society* pp 5174–7
[47] Kung T A, Langhals N B, Martin D C, Johnson P J, Cederna P S and Urbanchek M G 2014 Regenerative peripheral nerve interface viability and signal transduction with an implanted electrode *Plast. Reconstr. Surg.* **133** 1380–94
[48] Frost C M *et al* 2018 Regenerative peripheral nerve interfaces for real-time, proportional control of a neuroprosthetic hand *J. Neuroeng. Rehabil.* **15** 108

[49] Vaskov A K *et al* 2022 Surgically implanted electrodes enable real-time finger and grasp pattern recognition for prosthetic hands IEEE Trans. Robot. **38** 2841–57
[50] Light C M, Chappell P H and Kyberd P J 2002 Establishing a standardized clinical assessment tool of pathologic and prosthetic hand function: normative data, reliability, and validity *Arch. Phys. Med. Rehabil.* **83** 776–83
[51] Mathiowetz V, Volland G, Kashman N and Weber K 1985 Adult norms for the box and block test of manual dexterity *Am. J. Occup. Ther.* **39** 386–91
[52] Kontson K, Marcus I, Myklebust B and Civillico E 2017 Targeted box and blocks test: normative data and comparison to standard tests *PLoS One* **12** e0177965
[53] Hebert J S, Lewicke J, Williams T R and Vette A H 2014 Normative data for modified box and blocks test measuring upper-limb function via motion capture *J. Rehabil. Res. Dev.* **51** 918–32
[54] Liu J, Zhang D, Sheng X and Zhu X 2014 Quantification and solutions of arm movements effect on sEMG pattern recognition *Biomed. Signal Process. Control* **13** 189–97
[55] Mastinu E, Ahlberg J, Lendaro E, Hermansson L, Hakansson B and Ortiz-Catalan M 2018 An alternative myoelectric pattern recognition approach for the control of hand prostheses: a case study of use in daily life by a dysmelia subject *IEEE J. Transl. Eng. Health Med.* **6** 2600112
[56] Todorov E, Erez T and Tassa Y 2012 MuJoCo: a physics engine for model-based control *2012 IEEE RSJ Int. Conf. on Intelligent Robots and Systems* pp 5026–33
[57] Ross T P, Calhoun E, Cox T, Wenner C, Kono W and Pleasant M 2007 The reliability and validity of qualitative scores for the controlled oral word association test *Arch. Clin. Neuropsychol.* **22** 475–88
[58] Simon A M, Hargrove L J, Lock B A and Kuiken T A 2011 The target achievement control test: evaluating real-time myoelectric pattern recognition control of a multifunctional upper-limb prosthesis *J. Rehabil. Res. Dev.* **48** 619–27
[59] Birdwell J A, Hargrove L J, Weir R F F and Kuiken T A 2015 Extrinsic finger and thumb muscles command a virtual hand to allow individual finger and grasp control *IEEE Trans. Biomed. Eng.* **62** 218–26
[60] Gates D H, Walters L S, Cowley J, Wilken J M and Resnik L 2016 Range of motion requirements for upper-limb activities of daily living *Am. J. Occup. Ther.* **70** 7001350010p1–10
[61] He J, Zhang D, Jiang N, Sheng X, Farina D and Zhu X 2015 User adaptation in long-term, open-loop myoelectric training: implications for EMG pattern recognition in prosthesis control *J. Neural Eng.* **12** 046005
[62] Montagnani F, Controzzi M and Cipriani C 2015 Is it finger or wrist dexterity that is missing in current hand prostheses? *IEEE Trans. Neural Syst. Rehabil. Eng.* **23** 600–9