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A Case Series in Position-Aware Myoelectric Prosthesis Control using Recurrent Convolutional Neural Network Classification with Transfer Learning

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***Abstract*— Position-aware myoelectric prosthesis controllers require long, data-intensive training routines. Transfer Learning (TL) might reduce training burden. A TL model can be pre-trained using forearm muscle signal data from many individuals to become the starting point for a new user. A recurrent convolutional neural network (RCNN)-based classifier has already been shown to benefit from TL in *offline* analysis (95% accuracy). The present *real-time* study tested whether an RCNN-based classification controller with TL (RCNN-TL) could reduce training burden, offer improved device control (per functional task performance metrics), and mitigate what is known as the "limb position effect". 27 participants without amputation were recruited. 19 participants performed wrist/hand movements across multiple limb positions, with resulting forearm muscle signal data used to pre-train RCNN-TL. 8 other participants donned a simulated prosthesis, retrained (calibrated) and tested RCNN-TL, plus trained and tested a conventional linear discriminant analysis classification controller (LDA-Baseline). Results confirmed that TL reduces user training burden. RCNN-TL yielded improved task performance durations over LDA-Baseline (in specific Grasp and Release phases), yet other metrics worsened. Overall, this work contributes training condition factors necessary for TL success, identifies metrics needed for comprehensive control analysis, and contributes insights towards improved position-aware control.**

I. INTRODUCTION

Individuals with a transradial amputation often use myoelectric prostheses to restore or assist their impaired upper limb function. Prosthetic devices enable users to perform everyday tasks like eating, grooming, and getting dressed. Accomplishing such tasks requires execution of prosthetic hand and wrist movements in varied limb positions. These movements are driven by motors housed within the device, with instructions sent to the motors by a controller. Wearers operate their prosthesis using residual limb muscle contractions, and surface electrodes in its socket capture resulting muscle signals using electromyography (EMG) [1]. Myoelectric controllers, including those that use pattern recognition, can interpret EMG signals. When pattern recognition is employed for control, a prosthesis wearer must perform a series of specific movements, known as a training routine, prior to using their device [2]. Once a training routine is complete, patterns evident in the captured signal features are learned by the control model, the features are classified during device use, and the resulting classifications inform motor instructions. Pattern recognition-based myoelectric controllers are commonly tested in research settings and are commercially available, but are not yet widely accepted clinically.

Research has shown that EMG signals alone might not reliably inform intended prosthesis movement, particularly during instances when a user must hold their arm in untrained positions to accomplish tasks [3]. Limb position variations can result in degraded pattern recognition-based control, as evidenced by unexpected device movements and reported user frustration [3]. This challenge is known as the "limb position effect". To mitigate this effect, some researchers have increased the number of surface EMG electrodes worn by users (high-density electrode arrays) [4]. Other researchers have successfully introduced the addition of an inertial measurement unit (IMU), worn on a user's residual forearm for the capture of supplemental limb position data [5]. By combining EMG and IMU data, a *position-aware* pattern recognition-based controller can indeed provide reliable function across multiple limb positions [6].

To effectively mitigate the limb position effect, a control model training routine must include hand/wrist movements performed across multiple limb positions—not simply performed in a bent-elbow position as required by conventional controllers [6]. The time and muscle activation demands of such a routine, however, become burdensome for the user [1], [7]. In addition, retraining (or calibration) is typically required of myoelectric controllers in instances when device control degrades, such as due to muscle fatigue or electrode shifts. This retraining further contributes to user training burden. Overall, mitigation of the limb position effect necessitates a burdensome and data-intensive control model solution.

Commercially available myoelectric controllers that employ pattern recognition typically use a statistical model known as linear discriminant analysis (LDA) [5], [8]. An LDA classification control model applies probability theory to discover patterns in EMG data, and then uses engineered

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features to inform control. Given that LDA-based control is commonly used in myoelectric prostheses, it has been adopted in research as a baseline for comparison to other controllers [6]. An emerging area of research that offers an alternative to LDA solutions uses deep learning [9]; in particular, recurrent convolutional neural networks (RCNNs) [6]. RCNNs offer the ability to learn new useful features from raw EMG signals (rather than requiring features to be extracted prior to pattern learning) and the ability to recognize the nuances of the time-varying behaviour of EMG signals [9]. RCNN classification has been investigated for position-aware prosthesis control, because it can combine large amounts of data from multiple sensors, including from EMG and IMU data streams [6].

Transfer learning (**TL**) is an adjunct solution that may reduce the training and retraining burden placed upon a user, as necessitated by position-aware RCNN-based classification control (but not applicable to LDA-based control). With this solution, a classification control model (classifier) can be trained using a large dataset of EMG and IMU signals obtained from numerous individuals, to become the starting point for a new user's device control. That new user would require only a reduced amount of personal movement data for training and retraining thereafter. Our earlier offline research determined that an RCNN-based classifier can indeed benefit from TL [10]. It relied on the capture of a large dataset of muscle data points for control pre-training. Our RCNN-based classifier with TL achieved 95% accuracy in movement classification. This classifier was pre-trained using data from 19 participants and required just 4 seconds of data per movement in three limb positions for retraining. The favourable results of this earlier work showed both high classification accuracy and decreased training burden.

Still, it has been shown that offline myoelectric prosthesis research outcomes do not necessarily correlate with physical device controllability [11]. Our earlier work, therefore, could be furthered through real-time research—that is, through the use of a donned simulated prosthesis. Such devices have been shown to be a good proxy for actual myoelectric prosthesis use [12]. Experimentation using a simulated device could confirm whether an RCNN-based classification controller with TL can mitigate the limb position effect and decrease training burden. To conduct this real-time research: (1) testing should include use of a donned simulated prosthesis, (2) a training routine should include multi-position hand and wrist movements, (3) functional tasks should be used for testing, and (4) established kinematic metrics should be used for outcome analysis.

The present study bridges the gap between reported offline myoelectric control outcomes and real-time device controllability when an RCNN classification controller with TL (**RCNN-TL**) is systematically compared to an LDA baseline classification controller (**LDA-Baseline**). Here, a simulated prosthesis was worn by participants without amputation, each of whom executed training routines and performed functional tasks across varying limb positions to test control. This work contributes to the literature by offering valuable lessons towards addressing the limb position effect. We investigated whether TL can indeed reduce user training burden in conjunction with RCNN-based classification. Important implications were discovered regarding the conditions required for training, and the need for comprehensive metrics to fully interpret control results.

II. METHODS

A. *Participants*

Two distinct groups of participants were recruited for this study: a General Participant Group, whose data was used to pre-train RCNN-TL's model, and a Simulated Prosthesis (SP) Participant Group, who further trained and tested both RCNN-TL and LDA-Baseline. All participants provided written informed consent, as approved by the University of Alberta Health Research Ethics Board (Pro00086557).

General Participant Group *(without simulated prosthesis)***:** Nineteen participants without upper limb impairment were recruited. All had normal or corrected vision, 10 were male, nine were female, 17 were right-handed. They had a median age of 25 years (range: 19–58 years) and median height of 170 cm (range: 159–193 cm).

SP Participant Group *(with donned simulated prosthesis)***:** A total of nine new participants without upper limb impairment were recruited. One participant was removed due to their inability to reliably control the donned simulated prosthesis even after control practice. Of the remaining eight participants, all had normal or corrected vision, five were male, three were female, seven were right-handed. They had a median age of 22 years (range: 20–56 years) and median height of 181 cm (range: 169–185 cm). No participants had experience with EMG pattern recognition control using a simulated prosthesis. The eight participants completed two data collection sessions on different days (with a median of 24 days between sessions, range: 18–45 days), during which half of the participants used RCNN-TL in their first session, and the other half used LDA-Baseline in their first session. Participants used the other controller in their second session.

B. *EMG and Accelerometer Data Collection*

Each participant in both groups wore a Myo gesture control armband (Thalmic Labs, Kitchener, Canada—discontinued) at approximately the upper third of their forearm (with the top of the armband at a median of 27.83% of the way down the forearm from the medial epicondyle to ulnar styloid process), as shown in Figure 1A. The Myo armband contained eight surface electrodes to collect EMG data at 200 Hz. The Myo armband also contained one IMU to collect limb position data (three accelerometer, three gyroscope, and four quaternion data streams) at 50 Hz. Myo Connect software was used to stream EMG and IMU data into Matlab.

C. *Donned Simulated Prosthesis*

The simulated prosthesis used in this study was the 3D-printed Modular-Adaptable Prosthetic Platform (MAPP) [13]

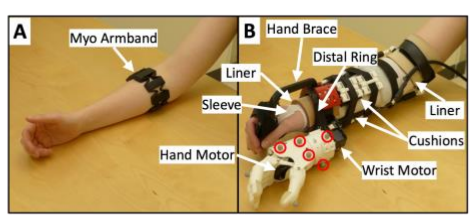

Figure 1. (A) Myo armband on a participant's forearm and (B) donned simulated prosthesis on a participant's forearm, with labels indicating the sleeve, 2 pieces of liner, hand brace, distal ring, cushions, wrist motor, and hand motor. Five motion capture markers are indicated with red circles.

(shown in Figure 1B). It was fitted to each SP Participant Group member's right arm for simulation of transradial prosthesis use. The MAPP's previously-published design [13] was altered to improve wearer comfort in our study—the distal ring was made to resemble the oval shape of a wrist and the hand brace was elongated so that the distal ring would sit more proximally on the wearer's wrist. A 3D-printed robotic hand [14] was affixed to the MAPP beneath the participant's hand. Wrist rotation capabilities were also added to the device. Hand and wrist movements were each powered by a Dynamixel MX Series motor (Robotis Inc., Seoul, South Korea).

After placement of the Myo armband, each SP Participant Group member donned a thin sleeve and then the MAPP. To increase participant comfort, pieces of thermoplastic elastomer liner were placed inside the distal ring and just above the participant's elbow, and 3D-printed cushions, made of Ninjaflex Cheetah filament (Ninjatek, Inc.), were placed throughout the device socket (shown in Figure 1B). The secureness of the device and each participant's comfort were checked before proceeding with controller training.

D. Control Model Implementation and Training

RCNN-TL Implementation: Bayesian optimization automatically determined the number of convolution layers, number of filters, filter size, pooling size, and patience required for the classifier used in this controller. Optimization was performed in two steps: first, the number of layers along with each hyperparameter being optimized were determined using a broad range of values; thereafter, values were refined using a narrower range (centered at earlier optimized values). RCNN-TL's model architecture consisted of 19 layers, as illustrated in Figure 2. In this model, a sequence input layer first received and normalized the training data. Then, a sequence folding layer was used, allowing convolution operations to be performed independently on each window. This was followed by a block of four layers: a 2D convolution, a batch normalization, a rectified linear unit (ReLU), and an average pooling layer. This block of layers was repeated once more. Each of the two average pooling layers had a pooling size of 1x4. A block of three layers followed: a 2D convolution, a batch normalization, and a ReLU layer. The optimal number of filters in the convolution layers were determined to be 4, 16, and 32, respectively, and each had a filter window size of 1x3. The next layers included a sequence unfolding layer (to restore the sequence structure), a flatten layer, a long short-term memory (LSTM) layer, and a fully connected layer. Finally, a softmax layer and classification layer were used. To prevent overfitting, a patience parameter was set to trigger early stopping when the validation loss increased five times (e.g., similar to Côté-Allard et al. [15]).

RCNN-TL's Model Pre-Training Routine: General Participant Group members followed onscreen instructions, performing muscle contractions in 5 wrist positions, for 5 seconds each: flexion, extension, pronation, supination, and rest. The muscle contractions were performed twice in 4 limb positions: arm at side, elbow bent at 90°, arm straight out in front at 90°, and arm up 45° from vertical. This position-aware routine was similar to those used in other real-time control studies aiming to mitigate the limb position effect [5], [6], [11]). The resulting EMG and accelerometer data, plus corresponding classes of muscle contractions, were used to pre-train RCNN-TL's model.

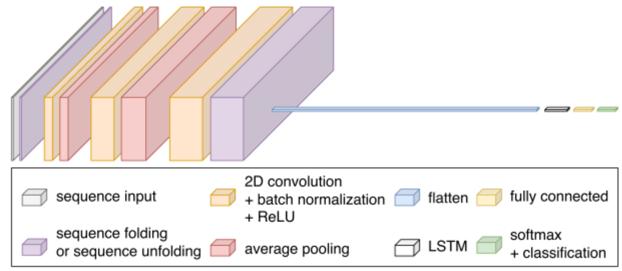

Figure 2. Architecture of RCNN-TL's model: sequence input layer; sequence folding layer; two blocks of 2D convolution, batch normalization, rectified linear unit (ReLU), and average pooling; one block of 2D convolution, batch normalization, and ReLU; sequence unfolding layer; flatten layer; long short-term memory (LSTM) layer; fully connected layer; softmax layer; and classification layer.

RCNN-TL's Model Retraining Routine: SP Participant Group members followed onscreen instructions, performing muscle contractions in the same 5 wrist positions, for *only 2* (rather than 5) seconds each. The muscle contractions were performed twice in *only 3* (not 4) limb positions: arm at side, elbow bent at 90°, and arm up 45° from vertical. Note that this shortened/optimized routine was uncovered in our previous offline research [10]. The resulting EMG and accelerometer data, plus corresponding classes of muscle contractions, were used to retrain RCNN-TL's model.

LDA-Baseline Implementation: Four commonly used EMG features were chosen for implementation of LDA-Baseline's model: mean absolute value, waveform length, Willison amplitude, and zero crossings [16]. A pseudo-linear LDA discriminant type was used, given that columns of zeros were occasionally present in some classes for some features (including Willison amplitude and zero crossings).

LDA-Baseline's Model Training Routine: SP Participant Group members followed onscreen instructions, performing muscle contractions in the same 5 wrist positions, for 5 seconds each. The muscle contractions were performed twice, with the participants' elbow bent at 90°. This single-position routine mimicked standard myoelectric prosthesis training [3]. The resulting EMG data and corresponding classes of muscle contractions were used to train LDA-Baseline's model.

E. Data Processing

For both model training and real-time control, the EMG data from the Myo armband were filtered using a high pass filter at 20 Hz (to remove movement artifacts), as well as a notch filter at 60 Hz (to remove electrical noise). Next, the accelerometer data streams were upsampled to 200 Hz (using previous neighbour interpolation) to align them with the corresponding EMG data. Data were then segmented into windows (160-millisecond with a 40-millisecond offset). These windows of EMG and accelerometer data were used for RCNN-TL. For LDA-Baseline, time-domain features were calculated for each EMG channel, in each window. Each model was trained in Matlab using an Intel Core i9-10900K CPU (3.70 GHz) with 128 GB of RAM. RCNN-TL's and LDA-Baseline's models were retrained/trained in median times of 3.41 and 0.39 seconds, respectively. For real-time control, the classifiers predicted wrist and hand movements in Matlab, predictions were relayed to brachI/Oplexus [17], and control signals were sent to the simulated prosthesis' motors.

F. Control Practice

Each SP Participant Group member took part in a control practice period. They were taught how to operate the simulated prosthesis using their muscle contractions. This control practice took approximately 40 minutes.

To determine whether participants could reliably control the simulated prosthesis, they completed an activity. Two cups were situated in front of them at two different heights, with a ball in one of the cups. Participants were asked to pour the ball between the two cups, and instances when the participants dropped the ball or a cup were recorded. If participants could not complete at least 10 pours with a success rate of at least 75% within 10 minutes, they were removed from the study. Recall that one participant was removed (as stated in Section II.A), given that they could not complete this activity with LDA-Baseline in their first session.

G. Motion Capture Setup

An 8-camera OptiTrack Flex 13 motion capture system (Natural Point, OR, USA) was used to capture hand movements and task objects at 120 Hz. Six individual markers were placed on the simulated prosthesis hand to ensure reliable rigid body tracking (with at least 3 markers always trackable), five of which are shown in Figure 1B. Note that unlabelled markers in Figure 1B were not used for analysis.

H. Functional Tasks for Control Testing

Pasta Box Task (Pasta): Participants were required to pick up a box of pasta and move it between a side table and two shelves at varying heights on a cart (including across their midline), and then back to the side table [18], as shown in Figure 3A. Motion capture markers were placed on the cart, side table, and pasta box, as per Valevicius et al. [18]. Participants performed a total of 10 Pasta trials. If participants dropped the pasta box, placed it incorrectly, performed an incorrect movement sequence, or hit the frame of the task cart, the trial was labelled as an error and not analyzed.

Refined Clothespin Relocation Test (RCRT): Participants were required to move three clothespins between targets on horizontal and vertical bars [19], as shown in Figure 3B,C. To simplify trial execution, RCRT was split into **RCRT Up** and **RCRT Down** trials. During Up trials, participants moved the clothespins from the horizontal bar (right to left positions) to the vertical bar (bottom to top positions), as shown in Figure 3B. During Down trials, participants moved the clothespins from the vertical bar to the horizontal bar, in the same order as in Up trials, as shown in Figure 3C. A height adjustable cart was set such that the top of each participants' shoulder was aligned with the midpoint between the top two targets on the vertical bar, as shown in Figure 3D. Five motion capture markers were placed on the cart, three on the task base, and one on each clothespin. Participants performed a total of 10 Up trials and 10 Down trials. If participants dropped a clothespin, placed it incorrectly, or performed an incorrect movement sequence, the trial was labelled as an error and not analyzed.

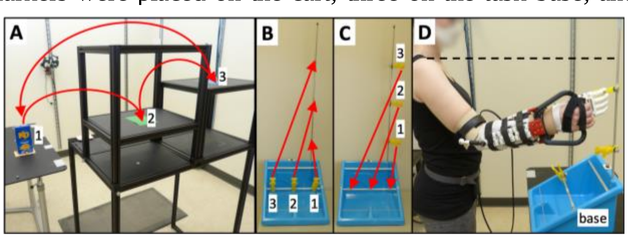

Figure 3. (A) Pasta Box Task trial movement order; and Refined Clothespin Relocation Test (B) Up trial movement order, and (C) Down trial movement order, and (D) adjustable cart setup.

I. Experimental Data Analysis

Motion capture data analysis in this study was conducted in accordance with Valevicius et al. [18]: the marker trajectory data were cleaned and filtered; for each task, the data from each trial were divided into distinct ***movements*** based on hand velocity and the velocity of the pasta box/clothespins; the data from each movement were further segmented into the ***phases*** of Reach, Grasp, Transport, Release, and Home (the Home phase was not used for data analysis); and ***movement segments*** of Reach-Grasp and Transport-Release were used in hand movement analysis.

Commonly used task performance metrics were calculated as per Valevicius et al. [18]: task success rate (the percentage of trials that were error-free) was calculated for each *task*; trial duration was calculated for each *trial*; phase duration and relative phase duration were calculated for each *phase*; and peak hand velocity, hand distance travelled, and hand trajectory variability were calculated for each *movement segment.*

To investigate task performance differences between RCNN-TL and LDA-Baseline, the following statistical analyses were performed:

Task success rate—Pairwise comparisons (t-test or Wilcoxon sign rank test) were conducted and deemed significant when the p value was less than 0.05.

Trial duration—Participants' results were averaged across trials, after which pairwise comparisons between the controllers were conducted.

All other metrics—Participants' results were averaged across trials and movements. If results were normally-distributed, a two-factor repeated-measures analysis of variance (RMANOVA) was conducted using the factors of controller and phase/movement segment. When the resulting controller effects or controller-phase/movement segment interactions were deemed significant (that is, when the Greenhouse-Geisser corrected p value was less than 0.05), pairwise comparisons between the controllers were conducted. If results were not normally-distributed, the Friedman test was conducted. When the resulting p value was less than 0.05, pairwise comparisons between the controllers were conducted.

III. Results

The functional task performance metrics for RCNN-TL versus LDA-Baseline are shown in Figure 4. Significant differences are indicated with above-bar asterisks. Improvements in task performance are characterized by high success rates, low trial durations, low phase durations, high Reach and Transport relative phase durations, low Grasp and Release relative phase durations, high peak hand velocities, low hand distances travelled, and low hand trajectory variability, as per Valevicius et al. [18].

A. Significant Differences Between Controllers

Significant differences between RCNN-TL and LDA-Baseline were evident in 4 out of 48 total metrics. **RCNN-TL outperformed LDA-Baseline in 2 metrics**: Pasta Release

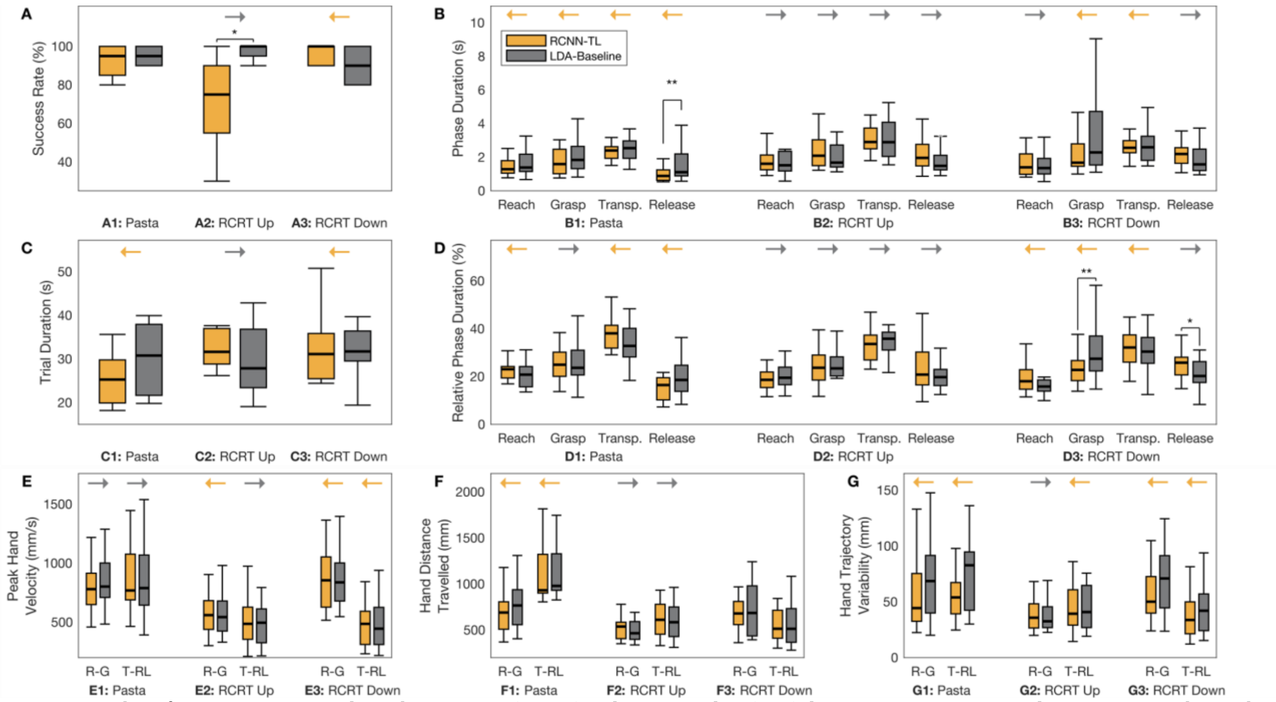

Figure 4. Task performance metrics results with RCNN-TL (orange) and LDA-Baseline (grey) during Pasta, RCRT Up, and RCRT Down tasks are shown for: (**A**) success rate, (**B**) phase duration, (**C**) trial duration, (**D**) relative phase duration, (**E**) peak hand velocity, (**F**) hand distance travelled, and (**G**) hand trajectory variability. Panels B and D present results in phases (Reach, Grasp, Transport [Transp.], Release) and Panels E–G present results in movement segments (Reach-Grasp [R-G], Transport-Release [T-RL]). Medians are indicated with thick lines, interquartile ranges are indicated with boxes, and significant differences between RCNN-TL and LDA-Baseline are indicated with asterisks (*: $p < 0.05$, **: $p < 0.01$). Arrows indicate which controller performed better for each metric, with orange left arrows indicating RCNN-TL and grey right arrows indicating LDA-Baseline.

phase duration (Figure 4B1) and RCRT Down Grasp relative phase duration (Figure 4D3). **LDA-Baseline outperformed RCNN-TL in 2 metrics**: RCRT Up success rate (Figure 4A2) and RCRT Down Release relative phase duration (Figure 4D3).

B. *Task-Specific Observations Between Controllers*

When considering *all* 48 task performance metrics (not simply those that exhibited significant differences) trends were evident for each of the three functional tasks (with 16 metrics per task). **Pasta:** 12 of 16 metrics showed that RCNN-TL performed better (indicated by left arrows in Figure 4B1–D1, F1, G1); 3 of 16 metrics showed that LDA-Baseline performed better (right arrows in Figure 4D1, E1); and success rate showed no change (Figure 4A1). **RCRT Up:** 2 of 16 metrics showed that RCNN-TL performed better (left arrows in Figure 4E2, G2); 14 of 16 metrics showed that LDA-Baseline performed better (right arrows in Figure 4A2–G2). **RCRT Down:** 11 of 16 metrics showed that RCNN-TL performed better (left arrows in Figure 4A3–E3, G3); 3 of 16 metrics showed that LDA-Baseline performed better (right arrows in Figure 4B3, D3); and hand distances travelled showed only small changes (both less than 6 mm differences, Figure 4F3).

IV. Discussion

This real-time study confirmed that TL reduces training burden when used with an RCNN-based classification controller [10]. Statistically, the functional task performance between RCNN-TL and LDA-Baseline was similar. However, compelling non-significant performance trends were identified, and many lessons were learned to direct future prosthesis control studies.

A. *TL Impact on Training Burden*

The General Participant Group members executed RCNN-TL's full pre-training routine, which took 3.33 minutes. The SP Participant Group members, however, simply executed RCNN-TL's 1-minute retraining routine prior to device control testing—a 70% decrease in duration. This research demonstrated that TL *is* a valuable adjunct to RCNN-based classification control, as it offers a model starting point that needs only to be calibrated using a smaller amount of individual-specific data. Notably, a TL solution is not possible with LDA-based control. To further investigate the influence of TL, we will examine an RCNN-based controller *without TL* in future work (using this study's model architecture).

B. *Pre-Training Conditions*

Despite our promising TL-based training burden reduction results, most task performance metrics did not yield significant control improvements. A realization from this outcome points to the principle that pre-training data should be captured under conditions that closely resemble those during use. The General Participant Group members performed wrist/hand movements while not wearing a simulated prosthesis for RCNN-TL pre-training. The SP Participant Group members, however, wore a simulated prosthesis when retraining RCNN-TL and training LDA-Baseline. The training conditions between the participant groups were somewhat dissimilar, as the donned prosthesis introduced weight, and co-activation of muscles resulted [20]. Consequently, patterns learned from the muscle signals of participants without the donned simulated prosthesis may not have optimally transferred to conditions for device use. Future research should investigate whether prosthesis weight does, in fact, play a significant role in TL-based control. A fundamental lesson learned in this study is that pre-training data should ideally be collected under physical conditions that will create the same muscle co-activation patterns exhibited during device use.

C. Comprehensive Metrics Needed

In our earlier offline research, RCNN-TL's model achieved a classification accuracy of 95% [10] and LDA-Baseline's model achieved a classification accuracy of 85% [6], when tested in all limb positions. In this current real-time research, only two of the 48 task performance metrics showed RCNN-TL performing significantly better than LDA-Baseline—in Pasta Release phase duration and in RCRT Down Grasp relative phase duration. At first glance, these results might seem underwhelming and may simply point towards the notion that offline results are not always indicative of real-time control performance [11]. However, interesting limb position-related findings can be surmised from this work, all pointing to a need for more comprehensive control metrics for their verification:

(1) *RCNN-TL might offer improved position-aware control:* RCNN-TL tended to perform better than LDA-Baseline in tasks that required high limb position Grasps—instances where control expectedly deteriorates due to the limb position effect.

(2) *A large phase duration interquartile range (IQR) might indicate a limb position effect occurrence:* An instance where the limb position effect probably occurred was during RCRT Down Grasp phases, as evidenced by a large phase duration IQR under LDA-Baseline control (3.19 s, as shown in Figure 4B3). This large IQR was likely due to control difficulties introduced when clothespins were grasped from the vertical bar over increasing heights. Moreover, as the same IQR was considerably smaller under RCNN-TL control (1.33 s, shown in Figure 4B3), the limb position effect was seemingly mitigated by TL.

(3) *More conclusive control metrics are needed:* The metrics analyzed in this work could not definitively confirm the limb position effect instances suspected in (1) and (2) above. An examination of control characteristic metrics, such as number of grip aperture adjustments [14] and grip aperture plateau time [21], however, would offer a richer understanding of what occurred during Grasp phases and why. Furthermore, a clearer understanding of user-reported experiences would improve overall assessments of control.

V. Conclusion

The goal of position-aware myoelectric prosthesis control is to provide users with reliable device operation across *all* limb positions. As pattern recognition-based control solutions require the user to execute a training routine to inform the controller, solutions attempting to mitigate the limb position effect need lengthy and therefore burdensome routines. This research confirmed that TL can reduce such training burden. As a primary contribution, this paper offered important considerations for implementation of an RCNN-based classification controller with TL, be it for simulated or actual myoelectric prosthesis user research. It suggested that TL should work better when the physical conditions for pre-training and training are similar, particularly as a prosthetic device introduces muscle coactivation patterns. This work also identified the need for comprehensive metrics—to uncover control characteristics that can be mapped to user reported control experiences. Ultimately, this work offered insights towards feasible position-aware prosthesis control.

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