EVIDENCE THAT A DEEP LEARNING REGRESSION-BASED CONTROLLER MITIGATES THE LIMB POSITION EFFECT FOR AN INDIVIDUAL WITH TRANSRADIAL AMPUTATION

Heather E. Williams[1,2], Jacqueline S. Hebert[1,3], Patrick M. Pilarski*[2,3], Ahmed W. Shehata*[1,3]

[1]Dept. of Biomedical Engineering, University of Alberta, Edmonton, Canada; [2]Alberta Machine Intelligence Institute (Amii), Edmonton, Canada; [3]Dept. of Medicine, University of Alberta
** These authors contributed equally to this work.*

ABSTRACT

Myoelectric upper limb prostheses provide wrist and hand movements to users yet remain somewhat unreliable and challenging to operate in high and cross-body limb positions. Hand and wrist movements are typically controlled sequentially and at a pre-set velocity. We have made significant inroads towards developing a novel controller that is reliable in multiple limb positions and offers fluid movements. Our recent work unveiled a promising *deep learning regression-based myoelectric control solution*. Herein we present results from our current study that tested device control using our solution versus a baseline (*classification*) alternative. A myoelectric prosthesis user with transradial amputation donned an experimental prosthesis and performed two functional tasks under each control option. The user exhibited superior device controllability across multiple limb positions using our regression-based solution. This work contributes evidence that a deep learning regression control approach can elicit accurate, simultaneous, and proportional device movements, while mitigating the limb position effect for a transradial prosthesis user.

INTRODUCTION

A myoelectric prosthesis connects to a user's residual limb via a socket and is normally controlled using electromyography (EMG) signals. EMG signals are generated by residual muscle contractions, detected by surface electrodes within the socket, and transmitted to the device's onboard controller. Pattern recognition-based controllers decode these signals to predict the user's intended movements and send corresponding commands to the device's motors. The most advanced controllers generally use a classification algorithm (model), which predicts one device action (or class) at a time [1]. The resulting prosthetic limb movements are somewhat robotic and are delivered at a pre-set velocity. That is, the wrist and hand cannot inherently move together simultaneously or with varied velocity.

Typically, individuals with transradial amputation are capable of reliably performing a limited number of residual limb muscle contractions [1]. These distinct contractions are selected to control predetermined device grasp patterns (such as hand open or close) and wrist rotation [1]. To initialize their pattern recognition-based control model for daily use, they must first perform a pre-determined series of muscle contractions, known as a training routine. Through training, patterns observed in captured EMG signals are associated with corresponding device actions [2]. A prevalent control problem, known as the "limb position effect", results when users attempt to use their devices in untrained limb positions [3]. Oftentimes, users struggle to regain control in response to this problem. To mitigate the effect, a control model must be trained in multiple limb positions [3].

Pattern recognition-based control models can be developed using a recurrent convolutional neural network (RCNN) approach. RCNNs are a type of network architecture for *deep learning*, capable of learning directly from and handling large amounts of multimodal data [4]. These capabilities lend themselves to the capture of limb position data for improved device control. In our prior work, we merged EMG data with accelerometer data from an inertial measurement unit (EMG+IMU) using an RCNN [5, 6]. We also tested an EMG+IMU regression-based control model (RCNN-Reg) [6] and found that regression models can yield smooth device movements, given that they can predict multiple movements at once, each proportional to muscle contraction intensity and across multiple limb positions [5]. In that study, we compared RCNN-Reg to a classification-based alternative that is commonly used in control comparisons (linear discriminant analysis, LDA-Baseline) [6]. Model testing involved participants without amputation (with a simulated prosthesis donned, a reasonable proxy for a person with amputation [7]) who performed two functional tasks—the Refined Clothespin Relocation Test (RCRT) [8] and the Pasta Box Task [9]. Our work 1) found that RCNN-Reg mitigated the limb position effect; 2) substantiated that participants could perform simultaneous wrist rotation and hand open/closed movements at varied velocities, as offered by RCNN-Reg; and 3) reported that RCNN-Reg yielded better predictive accuracy than LDA-Baseline [5, 10].

This current paper extends our earlier RCNN-Reg control model work by testing its translatability to those with upper limb loss. To accomplish this, one individual with transradial amputation donned an experimental myoelectric prosthesis that was controlled by RCNN-Reg in one session and then by LDA-Baseline in a separate session. All experimentation methods from our earlier research study ([6]) were followed. We were excited to find that RCNN-Reg indeed provided accurate, simultaneous, and proportional device movements for an individual with amputation, while mitigating the limb position effect. As such, RCNN-Reg might well offer a valuable control model alternative to traditional classification-based approaches for consideration in future myoelectric control research.

METHODS

One participant with amputation was recruited for this study. She was female, with an age of 50 years, a height of 167 cm, and corrected-to-normal vision. She was right-handed prior to amputation. Two years prior to this study, she had a right-side transradial amputation. Her residual limb was 18 cm long with a circumference of 21 cm at the widest point. The participant typically used a myoelectric hand. She also had some at-home commercial pattern recognition-based prosthesis control experience with two degrees of freedom (wrist rotation and hand) at an estimated usage of 6 hours/day over 3 weeks. She provided written informed consent, as approved by the University of Alberta Health Research Ethics Board (Pro00086557). The participant trained and tested RCNN-Reg in her first session and LDA-Baseline in her second session, with 28 days between the two sessions. An overview of our equipment, experimentation methods, and control analysis metrics is illustrated in Figure 1. Full protocol details can be found in our earlier works [6, 10].

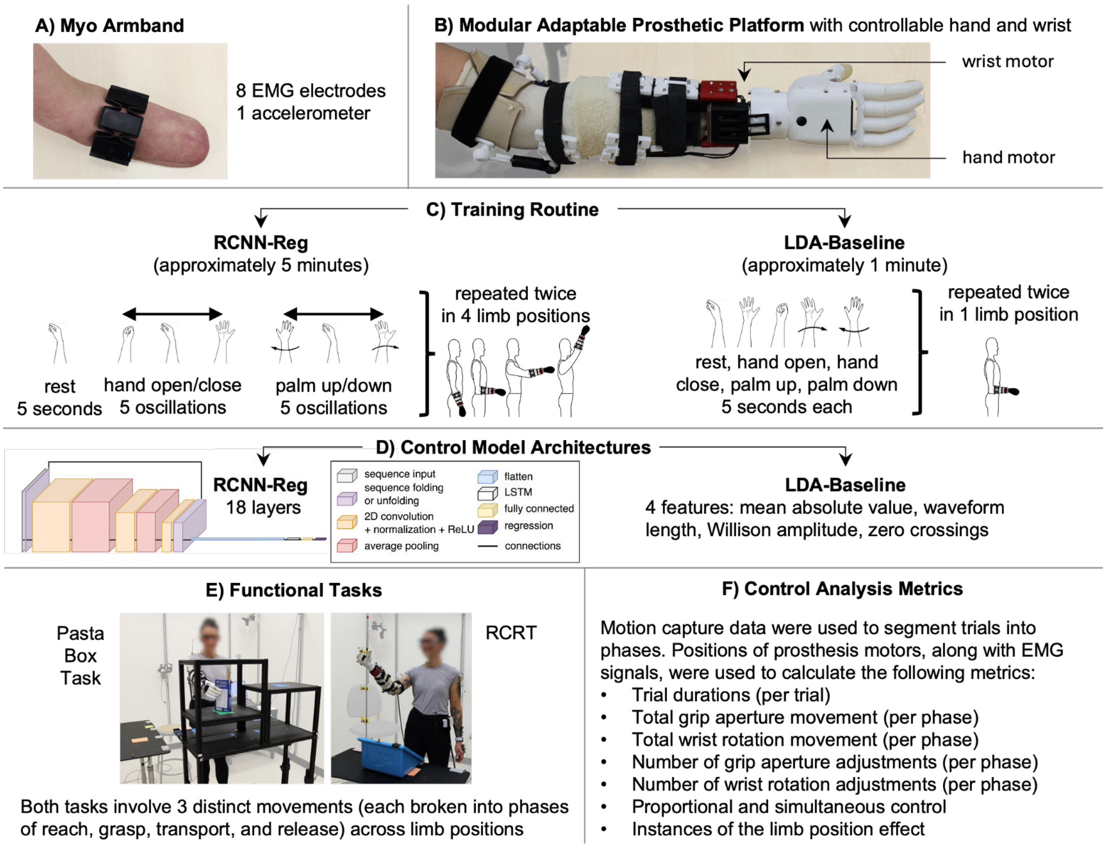

Figure 1: Equipment, experimentation, and analysis metrics in order of use: A) donned Myo armband, B) donned prosthesis [11], C) training routine employed for RCNN-Reg and LDA-Baseline models, including overall training durations [6], D) control model architecture details for RCNN-Reg and LDA-Baseline [6], E) functional tasks performed to test control—the Pasta Box Task [9] and the Refined Clothespin Relocation Test (RCRT) [8], split into RCRT Up and RCRT Down, and F) select metrics calculated for control analysis from our suite of metrics for comparative myoelectric prosthesis control [10].

RESULTS

RCNN-Reg yielded comparatively better myoelectric prosthesis control than LDA-Baseline. RCNN-Reg's improved control, barring a few exceptions, was evidenced by: 1) lower trial durations; 2) less total grip aperture and wrist rotation movement (indicators of corrections in mm and degrees, respectively); 3) simultaneous control of the prosthetic hand and wrist; along with 4) fewer grip aperture and wrist rotation adjustments (number of corrections). Results are illustrated in Figures 2A–F, respectively, with Figures 2A–C,2E–F showing exceptions where *some* grip and wrist rotation corrections were made by the participant. It was also apparent that the participant took advantage of RCNN-Reg's proportional control capabilities during task execution. That is, her hand and wrist movements occurred at a less-than-maximal velocity 100% of the time.

In our previous work [6], *under LDA-Baseline control, the limb position effect was identified a total of 13 times* (as determined through analysis of median and interquartile range trends [10]). Ten instances were evidenced during the Pasta Box Task (in 1 reach, 1 reach-grasp, 4 grasp, 2 transport, and 2 release metrics) and 3 instances during RCRT Down (all in grasp metrics). Conversely, in this present work, *under RCNN-Reg control, the limb position effect was identified a total of 3 times*, all during the Pasta Box Task (determined using our earlier work's analysis methods [10]). Such instances were evidenced in 1 reach metric and 2 transport metrics.

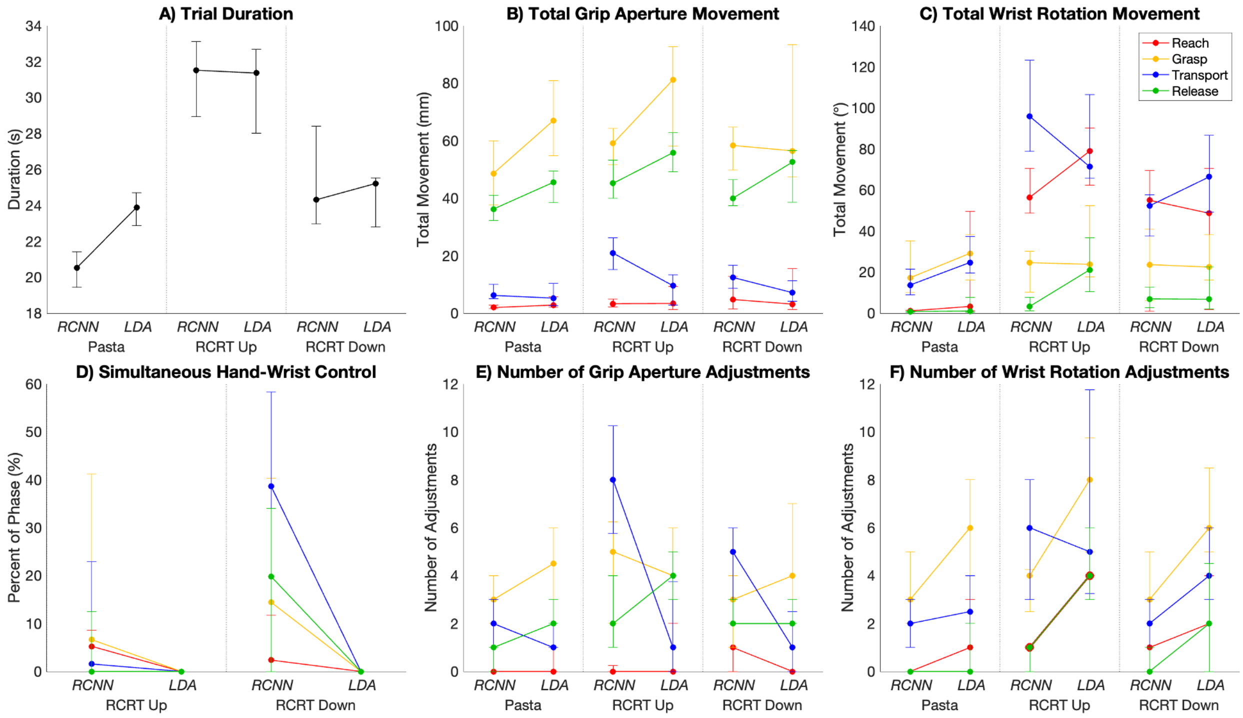

Figure 2: Controller comparison results (abbreviated as RCNN/LDA), including median A) trial duration, B) total grip aperture movement, C) total wrist rotation movement, D) simultaneous hand-wrist control, E) number of grip aperture adjustments, and F) number of wrist rotation adjustments. Medians are presented for each task, and for each phase (Reach in red, Grasp in orange, Transport in blue, and Release in green) where applicable. Interquartile ranges across trials are indicated with coloured error bars where applicable. Note that simultaneous hand-wrist control is only illustrated for RCRT Up/Down, as wrist rotation is not required in the Pasta Box Task (Pasta).

DISCUSSION & FUTURE WORK

Pasta Box Task Control Successes and Challenges: Although RCNN-Reg control was generally superior to LDA-Baseline, our participant exhibited some unexpected control challenges in the transport phases of the Pasta Box Task (Figure 2B,E's abovementioned control exceptions)—evidenced by increased total grip aperture movement and grip aperture adjustments. The Pasta Box Task requires a participant to transport a box in both cross-body and away-from-body limb positions (the specific instances where the limb position effect under RCNN-Reg control occurred). Notably, RCNN-Reg's training routine did *not* include these specific limb positions. Given these circumstances, the addition of cross-body and away-from-body limb positions to RCNN-Reg's training routine is advised. Future work should investigate which training positions improve device control.

RCRT Up and Down Control Successes and Challenges: When testing RCNN-Reg, our participant did not experience the limb position effect during execution of RCRT Up and Down. The effect was likely mitigated because RCNN-Reg's control model was trained in the same high limb positions required of these tasks. Despite this, the participant exhibited control challenges in transport phases of RCRT Up and Down (Figure 2B,C,E,F's abovementioned control exceptions)—evidenced by increased total grip aperture and wrist rotation movement, along with more grip aperture and wrist rotation adjustments, versus under LDA-Baseline control. These outcomes indicated her need to perform movement corrections to maintain control. RCRT's transport phases require a participant to rotate their wrist while not dropping the grasped clothespin, an inherently difficult movement. Although our participant experienced challenges, she appreciated the simultaneous control capabilities offered by RCNN-Reg in transport phases, as verbally reported: "It's neat that you can do it at the same time [simultaneous control], because you feel like you're losing it [starting to drop the clothespin while rotating the wrist] and you can try and grab it [adjust grip during wrist rotation]." Based on our participant's appreciation of these capabilities, and the fact that progressive learning needs to be allocated for complicated hand-tasks [12], we believe she could master simultaneous control and exhibit fewer adjustments in RCRT's transport phases if afforded more controller-use practice.

Training Routine Implications: RCNN-Reg's 5-minute training routine might prove to be burdensome for a user if repeated multiple times throughout the day (for re-calibration purposes). Future work should be undertaken to shorten the training routine duration. For instance, reducing the number of oscillations performed might be feasible. The incorporation of dynamic limb positions might also reduce routine duration *and* provide richer training data [13].

Future Experimentation: We recognize that our work did not exhaustively investigate RCNN-Reg. To corroborate our findings, the experimentation must be repeated by more participants with transradial amputation.

CONCLUSION

Our case study contributes, for the first time, evidence that an RCNN regression-based controller offers a user with transradial amputation control of their prosthetic wrist and hand simultaneously across multiple limb positions, using varied velocities. *RCNN-Reg successfully mitigated the limb position effect during device use,* given that our participant was able to retain control of their myoelectric prosthesis throughout numerous re-orientations of their limb in space during different tasks. Although regression-based control solutions have not garnered as much research attention as classification-based counterparts, the merits of RCNN-Reg, as presented in this paper, suggest that it be strongly considered as a future prosthesis controller.

ACKNOWLEDGEMENTS

We thank Quinn Boser, Thomas R. Dawson, Michael R. Dawson, and Albert Vette for data collection, data processing and/or experimental design assistance. This work was supported by Amii, the CIFAR AI Chairs program, NSERC DG RGPIN-2019-05961, and NSERC RGPIN-2023-04450.

REFERENCES

[1] P. Geethanjali, "Myoelectric control of prosthetic hands: State-of-the-art review," *Medical Devices: Evidence and Research*, vol. 9, pp. 247–55, 2016.

[2] E. Scheme, K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use," *J. Rehabil. Res. Dev.*, vol. 48, no. 6, pp. 643–59, 2011.

[3] E. Campbell, A. Phinyomark, E. Scheme, "Current trends and confounding factors in myoelectric control: Limb position and contraction intensity," *Sensors (Switzerland)*, vol. 20, no. 6, p. 1613, 2020.

[4] A. Phinyomark, E. Scheme, "EMG pattern recognition in the era of big data and deep learning," *Big Data and Cognitive Computing*, vol. 2, no. 3, p. 21, 2018.

[5] H. E. Williams, A. W. Shehata, M. R. Dawson, E. Scheme, J. S. Hebert, P. M. Pilarski, "Recurrent convolutional neural networks as an approach to position-aware myoelectric prosthesis control," *IEEE Trans. Biomed. Eng.*, vol. 69, no. 7, pp. 2243–55, 2022.

[6] H. E. Williams, A. W. Shehata, K. Y. Cheng, J. S. Hebert, P. M. Pilarski, "Myoelectric Prosthesis Control using Recurrent Convolutional Neural Network Regression Mitigates the Limb Position Effect," *bioRxiv*, 2024.

[7] H. E. Williams, C. S. Chapman, P. M. Pilarski, A. H. Vette, J. S. Hebert, "Myoelectric prosthesis users and non-disabled individuals wearing a simulated prosthesis exhibit similar compensatory movement strategies," *J. Neuroeng. Rehabil.*, vol. 18, p. 72, 2021.

[8] A. Hussaini, P. Kyberd, "Refined clothespin relocation test and assessment of motion," *Prosthet. Orthot. Int.*, vol. 41, no. 3, pp. 294–302, 2017.

[9] A. M. Valevicius, Q. A. Boser, E. B. Lavoie, G. S. Murgatroyd, P. M. Pilarski, C. S. Chapman, A. H Vette, J. S. Hebert, "Characterization of normative hand movements during two functional upper limb tasks," *PLOS ONE*, vol. 13, no. 6, p. e0199549, 2018.

[10] H. E. Williams, A. W. Shehata, K. Y. Cheng, J. S. Hebert, P. M. Pilarski, "A multifaceted suite of metrics for comparative myoelectric prosthesis controller research," *accepted to PLOS One*, 2024.

[11] B. W. Hallworth, A. W. Shehata, M. R. Dawson, F. Sperle, M. Connan, W. Friedl, B. Vodermayer, C. Castellini, J. S. Hebert, P. M. Pilarski, "A transradial modular adaptable platform for evaluating prosthetic feedback and control strategies," *Proc. MEC20*, pp. 203–6, 2020.

[12] J. M. Hahne, M. Markovic, D. Farina, "User adaptation in Myoelectric Man-Machine Interfaces," *Sci. Rep.*, vol. 7, p. 4437, 2017.

[13] A. Gigli, A. Gijsberts, C. Castellini, "Natural myocontrol in a realistic setting: A comparison between static and dynamic data acquisition," *Proc. ICORR*, pp. 1061–6, 2019.