PROPORTIONAL ELECTROMYOGRAPHIC CONTROL OF A BIONIC ARM IN A PARTICIPANT WITH CHRONIC HEMIPARESIS, MUSCLE SPASTICITY, AND IMPAIRED RANGE OF MOTION: A CASE STUDY

Caleb J. Thomson[1], Jacob A. George[1,2,3,4]

[1]*Department of Biomedical Engineering,* [2]*Department of Electrical and Computer Engineering,* [3]*Department of Mechanical Engineering,* [4]*Department of Physical Medicine and Rehabilitation, University of Utah, Salt Lake City, Utah, USA*

ABSTRACT

The long-term goal of this research is to restore intuitive and proportional motor control to stroke patients with an assistive exoskeleton. Stroke is the leading cause of disability in the United States, with 80% of stroke-related disability coming in the form of hemiparesis, presented as weakness or paresis on half of the body. Current electromyographic-(EMG)-controlled assistive exoskeletons do not allow for fine force regulation. That is, current control strategies provide only binary, all-or-nothing, control based on a linear threshold of EMG activity. In this case study with one hemiparetic stroke patient, we show that state-of-the-art EMG control algorithms can provide proportional control of a bionic arm despite weak and spastic muscle activity. The participant completed a virtual target-touching exercise with an EMG-controlled bionic arm by attempting to grasp (close) or extend (open) their hand. The participant completed the task under two conditions, with EMG from their paretic arm and with EMG from their healthy, contralateral arm. For grasping, there was no statistical difference in task performance for the paretic and healthy arms, but there was a significant decrease in the EMG signal-to-noise ratio for the paretic arm. For extension, there was a significant decrease in both task performance and EMG signal-to-noise ratio for the paretic arm. Despite these differences, the participant was still able to complete the target-touching task with the paretic arm. These preliminary results show it is possible, for at least some patients, to provide proportional control of assistive devices using weak and spastic EMG. Importantly, information regulating fine force output is still present in EMG despite a visually immobile arm due to hemiparesis. Future work will validate these findings with additional stroke patients with varying presentations of hemiparesis and move into controlling upper-limb exoskeletons.

INTRODUCTION

Stroke is the leading cause of disability in the United States, with more than 795,000 people suffering from a stroke each year. Eighty percent of stroke-related motor deficits are in the form of upper-limb hemiparesis [1]. Hemiparesis makes it difficult to complete activities of daily living and thereby reduces quality of life and autonomy. Upper-limb exoskeletons controlled by electromyography (EMG) have been shown to assist patients with hemiparesis in activities of daily living [2]. However clinical upper-limb exoskeletons typically use a binary, "all-or-nothing" control algorithm that makes it difficult to perform fine motor activities such as manipulating fragile objects. Previous studies investigating proportional EMG control from stroke patients have focused on force (torque) control of an elbow exoskeleton [3] and robot-assisted wrist movement [4]. However few studies have investigated the feasibility of proportional EMG control of the position of the hand for stroke patients.

Proportional control of myoelectric prostheses has been achieved through a variety of different algorithms, including k-nearest neighbors [5], support vector machines [6], Kalman filters [7], convolutional neural networks (CNNs) [8], [9], long-short term memory networks [10], and recurrent CNNs [11]. In this case study, we explored if a Kalman filter could also provide proportional control of a myoelectric prosthesis for a single patient with hemiparesis. We show that proportional control can be readily achieved using this widely-used algorithm despite significantly lower EMG signal-to-noise ratio and a visually immobile arm. We also show that, for at least some movements, the quality of the proportional control can be similar to that from healthy EMG.

METHODS

Human Subjects

This case study involved a single human subject. Informed consent and experimental protocols were carried out in accordance with the University of Utah Institutional Review Board. The participant was male, 44 years of age, and experienced a stroke four years prior to the study. At the time of the study, the participant had severe spastic hemiparesis on the left side of his body. The participant scored a 1 on the Manual Muscle Test, indicating no visible movement of the arm but a palpable tendon prominence and flicker contraction. The participant scored a 3 on the Modified Ashworth Scale, indicating a considerable increase in muscle tone that made passive movement of the hand difficult.

Signal Acquisition

Surface EMG (sEMG) from the participant was collected using a symmetric bilateral pair of custom EMG sleeves [8], such that each electrode roughly targeted the same muscle group across sleeves. EMG was sampled at 1 kHz and filtered using the Summit Neural Interface processor (Ripple Neuro Med LLC) as described in [7]. EMG features used for estimating motor intent consisted of the 300-ms smoothed mean absolute value on 528 channels (32 single-ended channels and 496 calculated differential pairs) calculated at 30 Hz, as described in [7].

EMG signal-to-noise ratio (SNR) was calculated by taking the mean absolute value of the EMG signal during movement and dividing it by the mean absolute value of the EMG signal during rest. EMG SNR was calculated for the 32 single-ended channels (i.e., one SNR value per each electrode for the sleeves on the right and left arms). EMG SNR was calculated separately for grasping (closing the hand) and extension (opening the hand).

Experimental Setup

The participant was instructed to mimic preprogramed movements of a virtual prosthetic arm (MSMS, John Hopkins Applied Physics Lab) with either their healthy or paretic arm. sEMG was recorded while the participant mimicked those movements (Fig. 1). Preprogramed movements included hand grasping (simultaneous flexion of D1-D5) and hand extension (simultaneous extension of D1-D5). Each movement consisted of a 0.7-s rise time, 3-s hold time, and a 0.7-s return to baseline, as described in [7], [9]. The participant completed ten trials of each movement. This exercise was completed separately for the healthy arm and the paretic arm.

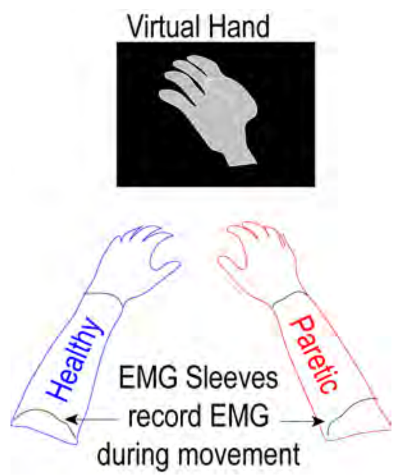

Figure 1: Experimental Setup. Participants were instructed to mimic the preprogramed movements of the virtual arm with their healthy arm or paretic arm. EMG activity was recorded using a symmetric bilateral pair of custom 32-electrode EMG sleeves.

EMG Control Algorithm

The EMG control algorithm used in this study was a modified Kalman Filter (MKF) [7]. The MKF provides an efficient recursive algorithm to optimally estimate the probability of hand movement when the likelihood model (i.e., the probability of the EMG activity given current hand position) and prior models (i.e., the state model of how position changes over time) are linear and Gaussian. In the implementation presented here, the MKF predicts the instantaneous position of the hand based on EMG activity of the arm at the current time point. The main difference between this study and [7] is that no threshold was applied to the output of the MKF.

Virtual Target-Touching Task

To evaluate proportional control of both arms, the participant completed a target-touching task controlling the virtual arm and attempting to move it into a target window. In this task the targets were placed at 50% of the maximum flexion and extension. Importantly, training data for the MKF was collected at 100% of the maximum flexion and extension, and thus, the task provides a measure of how well control extrapolates to novel intermediate positions. For each trial, the participant was instructed to stay within the target window for 5 seconds. The participant was instructed to relax between trials for 2 seconds for the healthy arm and 10 seconds for the paretic arm. The targets had a ±10% error tolerance, such that the participant received visual feedback indicating when they were within the target window.

The participant completed 20 trials of hand grasping and 20 trials of hand extension for both the healthy and paretic arms.

The root mean square error (RMSE) was calculated between the target window and the participant's kinematic output, such that values within the target window resulted in an RMSE of 0. The percent time within the target window (PTT) was calculated as the total time that the participant's kinematic output was within the target window out of the total duration of the task (five seconds).

Statistical Analysis

SNR, RMSE and PTT data were tested for normality using the Anderson-Darling test of normality. Paired t-tests were then performed between the healthy and paretic for each performance metric.

RESULTS

Paretic EMG had Lower SNR for Both Hand Grasping and Hand Extension

EMG activity during instructed hand grasping was visually similar between the paretic and healthy arms (Fig. 2A). In contrast, EMG activity during instructed hand extension was substantially less for paretic arm compared to the healthy arm (Fig. 2B). For both hand grasping and hand extension, SNR was significantly less for the paretic arm compared to the healthy arm (Fig. 2C).

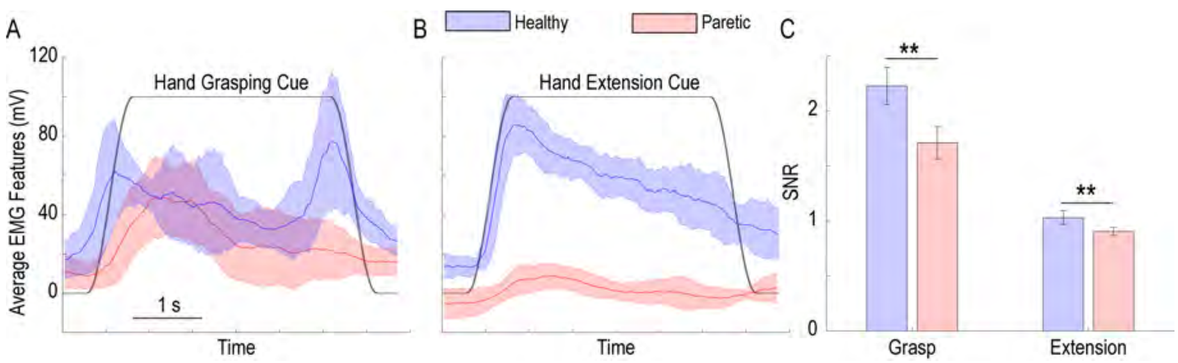

Figure 2. EMG activity from paretic and healthy arms during instructed hand grasping and hand extension. A) The average EMG feature (mean absolute value) of the healthy arm (blue) and the paretic arm (red) during instructed hand grasping (black line). Data show mean and standard deviation. B) The average EMG feature of the arm during instructed hand extension. C) SNR of the paretic EMG was lower than that of the healthy EMG for both movements. Data show SNR from the 32 electrodes for both the EMG sleeves on the paretic and healthy arms. Data show mean and standard error of the mean. ** $p<0.01$, paired *t*-test, n=32 electrodes.

Proportional Control Possible for Both Arms, but Worse for Paretic Hand Extension

The participant was able to complete the virtual target-touching task with EMG control from both their healthy and paretic arms. Kinematic output was similar between the paretic and healthy arms during instructed hand grasping (Fig. 3A). The average kinematic output was also similar between the paretic and healthy arms during instructed hand extension, however, kinematic output was less precise for the paretic hand, as evidenced by a larger standard deviation (Fig. 3B). For hand grasping, the participant had no significant differences between their paretic and healthy arms for RMSE (paretic arm 12.2% worse; Fig. 3C) and PTT (paretic arm 2.6% better; Fig. 3D). For hand extension, the participant's performance was significantly worse for their paretic arm compared to their healthy arm; RMSE was 128% worse (** $p<0.01$, paired t-test) and PTT was 52.4% worse (** $p<0.01$, paired t-test).

Importantly, despite significantly worse performance with the paretic arm for hand extension, the participant was still able to control the hand proportionally and complete the virtual target-touching task. The RMSE and PTT values reported here are similar to those found with amputees (RMSE means ~0.1; PTT means ~0.5 (Citterman et al., MEC 2022)) and healthy participants (RMSE mean ~0.15, PTT between 0.14 and 0.43) [12]. Thus, even the worst control the participant experienced was equivalent to that of other healthy participants. The participant was particularly excited about their ability to finely control the virtual bionic arm, despite the fact that his hand did not visually move. In a spontaneous moment of joy, the participant took out his phone to record a video of the virtual hand gently opening and closing.

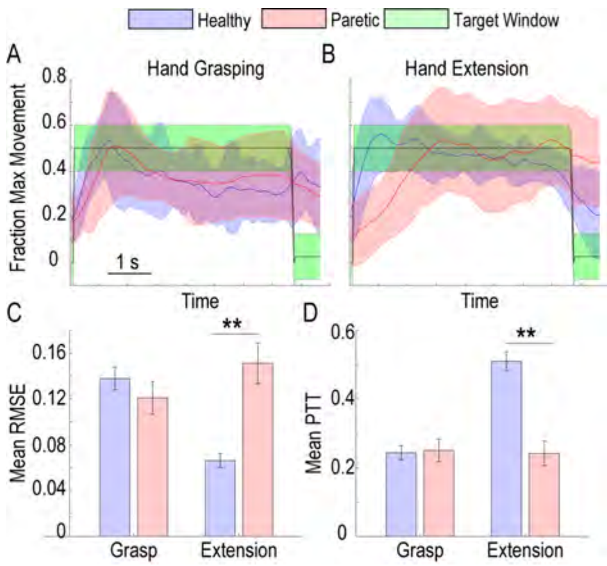

Figure 3. Performance of the virtual target-touching task for the healthy arm (blue) and paretic arm (red). A) Participant's kinematic output when attempting to perform a partial hand grasp (50% output). Data show the mean and standard deviation of the kinematic output across the 20 trials of the task. The green area represents the target window that the participant was attempting to remain within. B) Participant's kinematic output when attempting to perform partial hand extension (50% output). C) The RMSE between the participant's kinematic output and the target window was significantly greater for the paretic arm for hand extension (i.e., the paretic arm had significantly worse performance). No significant difference was found for hand grasping. Data show the mean and standard error of the mean across the 20 trials of the task. D) Similarly, the PTT was significantly less for the paretic arm for hand extension (i.e., the paretic arm had significantly worse performance). No significant difference was found for hand grasping.

CONCLUSSION

This case study with one participant shows promise in advancing and improving control for upper-limb exoskeletons for use after stroke. We specifically show that even though there are significant differences between the EMG signal between the healthy and paretic arms, widely-used myoelectric control algorithms can still extract useful information related to fine force regulation and provide proportional control in real-time. We also show that for at least some movements, performance can be equivalent to that of healthy EMG. Future work will extend this study to more participants and validate real-time proportional control with an exoskeleton manipulating fragile objects.

ACKNOWLEDGEMENTS

Research reported in this publication was supported by the Office of The Director (OD), Eunice Kennedy Shriver National Institute Of Child Health & Human Development (NICHD), and National Institute Of Dental & Craniofacial Research (NIDCR) of the National Institutes of Health (NIH) under Award Number DP5OD029571 awarded to J.A.G.

REFERENCES

[1] S. S. Virani *et al.*, "Heart Disease and Stroke Statistics—2021 Update," *Circulation*, vol. 143, no. 8, pp. e254–e743, Feb. 2021, doi: 10.1161/CIR.0000000000000950.

[2] G. J. Kim, L. Rivera, and J. Stein, "Combined Clinic-Home Approach for Upper Limb Robotic Therapy After Stroke: A Pilot Study," *Arch. Phys. Med. Rehabil.*, vol. 96, no. 12, pp. 2243–2248, Dec. 2015, doi: 10.1016/j.apmr.2015.06.019.

[3] T. Lenzi, S. M. M. De Rossi, N. Vitiello, and M. C. Carrozza, "Proportional EMG control for upper-limb powered exoskeletons," in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Aug. 2011, pp. 628–631. doi: 10.1109/IEMBS.2011.6090139.

[4] R. Song, K. Y. Tong, X. L. Hu, and X. J. Zheng, "Myoelectrically Controlled Robotic System That Provide Voluntary Mechanical Help for Persons after Stroke," in *2007 IEEE 10th International Conference on Rehabilitation Robotics*, Jun. 2007, pp. 246–249. doi: 10.1109/ICORR.2007.4428434.

[5] A. S. Dhawan *et al.*, "Proprioceptive Sonomyographic Control: A novel method for intuitive and proportional control of multiple degrees-of-freedom for individuals with upper extremity limb loss," *Sci. Rep.*, vol. 9, no. 1, Art. no. 1, Jul. 2019, doi: 10.1038/s41598-019-45459-7.

[6] A. T. Belyea, K. B. Englehart, and E. J. Scheme, "A proportional control scheme for high density force myography," *J. Neural Eng.*, vol. 15, no. 4, p. 046029, Jun. 2018, doi: 10.1088/1741-2552/aac89b.

[7] J. A. George, T. S. Davis, M. R. Brinton, and G. A. Clark, "Intuitive neuromyoelectric control of a dexterous bionic arm using a modified Kalman filter," *J. Neurosci. Methods*, vol. 330, p. 108462, Jan. 2020, doi: 10.1016/j.jneumeth.2019.108462.

[8] J. George, A. Neibling, M. Paskett, and G. Clark, "Inexpensive surface electromyography sleeve with consistent electrode placement enables dexterous and stable prosthetic control through deep learning," *MEC20 Symp.*, Jul. 2020, Accessed: Jul. 16, 2021. [Online]. Available: https://conferences.lib.unb.ca/index.php/mec/article/view/36

[9] J. A. George, M. R. Brinton, C. C. Duncan, D. T. Hutchinson, and G. A. Clark, "Improved Training Paradigms and Motor-decode Algorithms: Results from Intact Individuals and a Recent Transradial Amputee with Prior Complex Regional Pain Syndrome," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Jul. 2018, pp. 3782–3787. doi: 10.1109/EMBC.2018.8513342.

[10] C. J. Thomson, G. A. Clark, and J. A. George, "A Recurrent Neural Network Provides Stable Across-Day Prosthetic Control for a Human Amputee with Implanted Intramuscular Electromyographic Recording Leads," in *2021 43rd Annual International Conference of the IEEE Engineering in Medicine Biology Society (EMBC)*, Nov. 2021, pp. 6171–6174. doi: 10.1109/EMBC46164.2021.9629580.

[11] H. E. Williams, A. W. Shehata, M. R. Dawson, E. Scheme, J. S. Hebert, and P. Pilarski, "Recurrent Convolutional Neural Networks as an Approach to Position-Aware Myoelectric Prosthesis Control," *IEEE Trans. Biomed. Eng.*, pp. 1–1, 2022, doi: 10.1109/TBME.2022.3140269.

[12] H. Dantas, T. C. Hansen, D. J. Warren, and V. J. Mathews, "Shared Prosthetic Control Based on Multiple Movement Intent Decoders," *IEEE Trans. Biomed. Eng.*, vol. 68, no. 5, pp. 1547–1556, May 2021, doi: 10.1109/TBME.2020.3045351.