INVESTIGATION OF THE RELATIONSHIP BETWEEN HIGH DENSITY EMG DATA AND CLASSIFICATION ACCURACIES USING ABLE-BODIED AND TRANSRADIAL AMPUTEE PARTICIPANTS

Craig Prime[1,2], Usha Kuruganti[1,2], and Yves Losier[3,4,5]

[1]*Faculty of Kinesiology Department UNB, Fredericton, Canada*
[2]*Andrew and Marjorie McCain Human Performance Laboratory, UNB, Fredericton, Canada*
[3]*Department of Mechanical Engineering, UNB, Fredericton, Canada*
[4]*Department of Electrical and Computer Engineering, UNB, Fredericton, Canada*
[5]*Institute of Biomedical Engineering, UNB, Fredericton, Canada*

INTRODUCTION

Upper limb amputations significantly affect everyday activities and pose many functional limitations for individuals. Prostheses are often prescribed to help reduce these limitations and improve the individual's quality of life. Myoelectric controlled prostheses are currently being researched the most as they possess the most potential to improve an amputee's quality of life[1]. Current designs often use agonist and antagonist myoelectric signals (MES)[2] as inputs for the prosthetic limb's control system. This control scheme limits the number of movements that can be actuated by the prosthesis. As a result, numerous research groups have focused on both increasing the functionality of the prosthetic limb and assessing the clinical impact of multifunction control systems.

Due to advancements in technology and signal acquisition, pattern recognition is now deemed a viable option to increase the capabilities of the prosthetic limb. Pattern recognition incorporates the use of mathematical algorithms based on MES data. This application is capable of distinguishing different electrical patterns produced by multiple MES, which then actuate the desired prosthesis' movement[3,4]. The efficiency of myoelectric controlled prostheses are often assessed by calculating classification accuracies, i.e. how often a prosthesis is capable of performing the correct motion an individual is trying to produce. It is often difficult, however, to determine the relationship between the MES and prosthesis movements. This can be attributed to the input/output disconnect that is caused by the complex pattern recognition algorithm, i.e. the relationship is not linear. It is possible that this lack of a relationship between the two may be alleviated with a higher resolution of MES data which can be captured with the use of a high density electromyography (HD-EMG) system[5]. The purpose of this study was to collect preliminary data from both able-bodied participants and those with transradial (below elbow) amputations to further investigate the possible relationship between HD-EMG data and classification accuracy of the prosthetic limb. This data would lead to further investigations into the similarities and differences of muscle activation patterns between able-bodied individuals and transradial amputees. This topic is important to consider as many prosthesis control schemes are based on able-bodied individuals muscle activation patterns rather than the individuals who wear the devices. The work presented in this paper details the experimental protocol while also highlighting some of the preliminary results from this ongoing work.

METHODS

<u>Subjects</u>

Twenty able-bodied individuals between the ages of 20-60 were recruited to participate in this study. Two congenital amputees and one traumatic amputee have also participated, and depending on availability, two more transradial amputees will be recruited for this study (data collection is ongoing). Traumatic and congenital amputee participants are being recruited from the Institute of Biomedical Engineering at the University of New Brunswick. This project has been approved by the Research Ethics Board at the University of New Brunswick and is on file as REB 2012-132.

Instrumentation

A High Density EMG system (REFA 128 model, TMS International, REFA, Oldenzaal, The Netherlands) was used for this study's data collection. The HD-EMG system can measure up to 128 channels of monopolar EMG. A sampling frequency of 2000 Hz was used (TMSI User Manual). The electrophysiological variables are transferred via an optical fibre interface that communicates the signal to the PC. Signal filtering was performed using a 60-Hz notch filter to eliminate noise.

Electrode Placement

In this study, up to 64 HD-EMG electrodes were placed on the forearms of participants. An 8 by 8 grid was used on able-bodied individuals with the ground electrode located on C7 of the spine. The number of electrodes and the method of placement fluctuated for each participant as the length and proportions of their limbs varied.

The dimensions of the electrode grids were determined by measuring the circumference of the apex of the elbow and subsequently calculating the correct inter-electrode distance to allow the spacing between electrodes to be evenly spaced. The first electrode was placed at the proximal end of the elbow in the middle of the anterior side. Electrodes were then placed lateral to medial around the arm to generate the first row, which consisted of electrodes 1 to 8. The second row of electrodes, containing electrodes 9 to 16, were then placed distally to the first using the same lateral to medial orientation. The distance between rows was evenly distributed based on the length of the forearm or residual limb. The remaining six rows (3 to 8) followed the same procedure. Figure 1 provides an overview of the electrode placement.

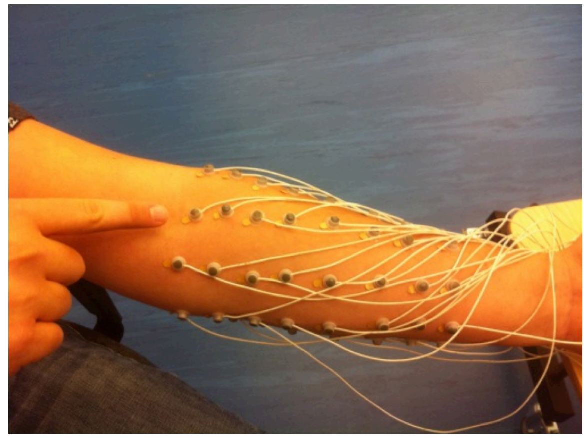

Figure 1: Anterior view of forearm (finger pointing at electrode 1)

Data Collection

Prior to electrode placement, participants were instructed on the purpose of the study and were given time to familiarize themselves with the 5 motions being used to evaluate the hypotheses. The motions of interest included: rest, closed hand, open hand, wrist pronation, and wrist supination. These motions were chosen because they have been used in previous research and are common movements used by upper limb prostheses[6,7]. Furthermore, a research occupational therapist, who works regularly with amputee patients, as well as the investigators involved with this research project have determined that these five motions display unique muscle activation patterns necessary to investigate the primary hypotheses. These motions were performed at three distinct contraction force levels (CFL): defined as a specific percentage of a participant's perceived subjective maximum force capability. The subjects were asked to produce contractions that reflected 20 – 40% of their maximum voluntary contraction (MVC) for a low CFL, between

40 – 60% MVC for a medium CFL and greater than 60% MVC for a high CFL.

Participants performed one trial of twelve 3 second contractions for each of the five motions, totalling 60 contractions. Of the twelve 3 second contractions within each motion, half were performed at the medium CFL level and the other half were divided into soft and hard CFL. More trials of medium contractions were needed because half of the medium contractions were used to train the LDA classifier being used[8] and the other half to test the medium CFL contractions. Participants were given approximately 15 to 20 seconds of rest between contractions. Amputee participants followed the same protocol as the able-bodied individuals, with the exception that breaks were necessary to avoid mental and physical fatigue, as well as to avoid cramping in their residual limb. Any deviations from the protocol were noted. The order for determining what CFL and what motion to perform was randomized.

PRELIMINARY RESULTS

EMG amplitudes were quantified using a root mean square (RMS) analysis. The results from the RMS analysis were then used to develop muscle activity maps in MATLAB. These activity maps use colour to indicate areas of high and low activity, with red areas indicating areas of high MES activity and blue areas indicated low areas of MES activity. An activity map from one able-body individual representing the three contraction force levels for the hand open motion are presented in Figure 2 and represent the average muscle activation pattern produced from three trials. These color maps provide a condensed visual representation of the trial data collected from the HD-EMG system. The preliminary data shows the quality of the data and indicates the areas of high muscle activity compared with low activity, and it can be seen that these areas change with increasing force levels. While limited in sample size, the preliminary data from those with amputations suggest similar pattern changes in the activity maps.

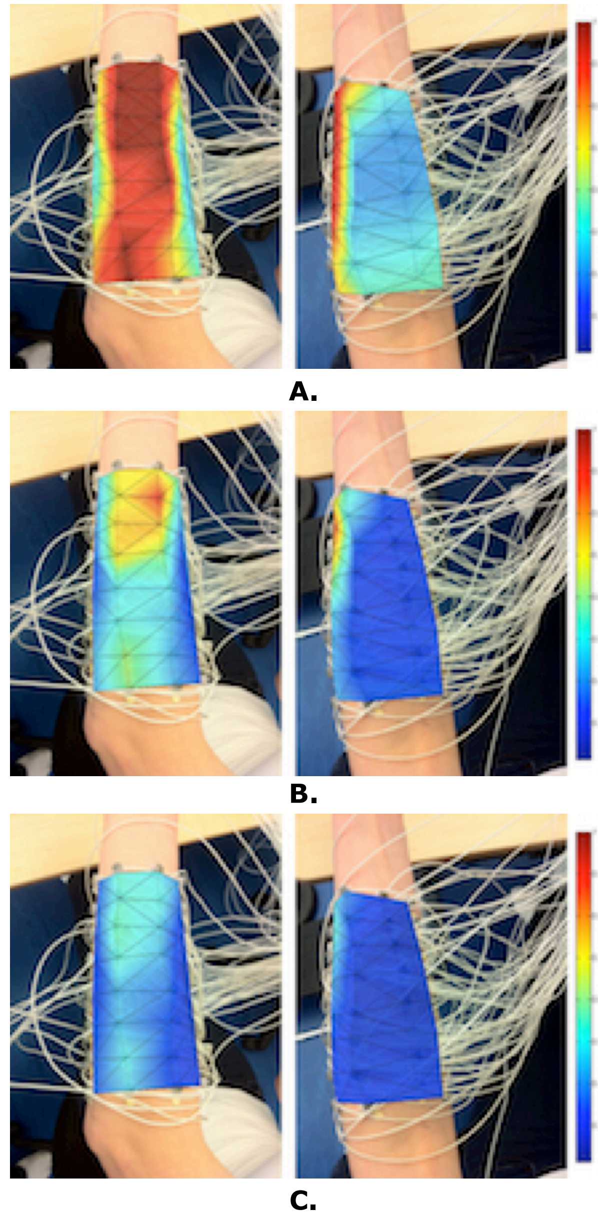

Figure 2: Hand open activity colormaps (A. hard contraction, posterior and anterior view; B. medium contraction, posterior and anterior view; C. soft contraction, posterior and anterior view)

CONCLUSION

This paper presented the ongoing development effort to quantify the relationship between the high density EMG distributions within targeted muscle regions and classification accuracies for both able-bodied and transradial amputee participants. Work is currently ongoing to complete the data collections with transradial amputees and to investigate pattern variations in the HD-EMG data. Once completed, the results will lead to a better understanding of how variations in the elicited muscle contractions affect classification accuracy and whether these relationships are similar for both the able-bodied and transradial amputee population.

ACKNOWLEDGEMENTS

This work was supported by the New Brunswick Limb Deficiency Clinic and the Natural Sciences and Engineering Research Council of Canada (NSERC).

REFERENCES

[1] E. Scheme and K Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use", *Journal of Rehabilitation Research & Development,* vol. 48(6), pp. 643-660, 2011.

[2] S. Watve, G. Dodd, R. MacDonald, and E. Stoppard, "Upper limb prosthetic rehabilitation", *Orthopaedics and Trauma,* vol. 25(2), pp. 135-142, 2011.

[3] P. Parker, K. Englehart and B. Hudgins, "Myoelectric signal processing for control of powered limb prostheses", *Journal of Electromyography and Kinesiology,* vol. 16(6), pp. 541-548, 2006.

[4] D. Graupe, J. Salahi, and K. Kohn, "Multifunctional prosthesis and orthosis control via microcomputer identification of temporal pattern differences in single-site myoelectric signals', *Journal of Biomedical Engineering,* vol. 4, pp. 17-22, 1982.

[5] J. van Dijk, J. Blok, B. Lapatki, I. van Schaik, M. Zwarts, and D. Stegeman, "Motor unit number estimation using high-density surface electromyography", *Clinical Neurophysiology,* vol. 119, pp. 33-42, 2008.

[6] H. Daley, K. Englehart, and U. Kuruganti,"Muscle activation patterns of the forearm: high-density electromyography data of normally limbed and transradial amputee subjects", *Journal of Prosthetics & Orthotics*, vol. 22(4), pp. 244-251, 2010.

[7] A. Simon, L. Hargrove, B. Lock, and T. Kuiken, "Target achievement control test: evaluating real-time myoelectric pattern-recognition of control of multifunctional upper-limb prostheses", *Journal of Rehabilitation Research & Development, vol.* 48(2), pp. 619-628, 2011.

[8] K. Englehart and B. Hudgins, "A robust-time control scheme for multifunction myolectric control," *IEEE transactions on Biomedical Engineering,* vol. 50(7), pp. 848-854, 2003.