MUSCLE ACTIVATION PATTERNS OF THE FOREARM: HIGH DENSITY EMG DATA OF NORMALLY LIMBED AND TRANSRADIAL AMPUTEE SUBJECTS

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INTRODUCTION

Myoelectric prosthetic devices have been accepted by upper limb amputees for many years. Advances in technology and improvement in design and comfort have contributed to growing user acceptance; however, there has been a limited amount of research using clinical populations to test advanced devices and control systems. Consequently, this study further investigated multifunction control of powered prostheses using upper limb amputee subjects. Clinical populations are the end user of prosthetic devices, therefore investigating their potential for success with multifunction control systems is necessary.

Several studies have shown that normally limbed subjects are capable of producing distinguishable muscle activation patterns for different movements (Hudgins et al. 1993). These activation patterns are repeatable across a number of trials and are essential for multifunction pattern recognition based myoelectric control. Using a high density (HD) electromyography (EMG) system, this study investigated muscle activation patterns of both normally limbed and amputee subjects for multiple wrist and hand movements. The purpose was to determine if distinct and repeatable muscle activation patterns are produced by upper limb amputees for different hand and wrist movements. It was hypothesized that muscle activation patterns generated from amputee data will differ from the standardized profiles of normally limbed subjects. However, it was also hypothesized that amputee subjects will be able to elicit distinct and repeatable patterns for at least a subset of the different movements.

METHODS

Participants

Both normally limbed and transradial amputee subjects participated in this study. Normally limbed participants (NL1 – NL6) had no history of neuromuscular disorders and they included three males and three females between the ages 21 and 27 years old. Transradial amputee subjects were recruited through the Institute of Biomedical Engineering at the University of New Brunswick. Two congenital amputees (CG1 and CG2) and one traumatic amputee (TR1) were included.

Table 1: Transradial Amputee Subject Information

Subject	Gender/ Age	Time since limb loss	Prosthetic Use
CG1	Female/ 17	N/A	User since 11months old. Uses a one site myoelectric control system.
CG2	Male/ 24	N/A	Not worn a prosthetic device in 10 years.
TR1	Female/ 41	13 years (due to Osteo-sarcoma)	One site myoelectric control system since time of amputation.

Instrumentation

A High Density (HD) EMG system (TMS International) was used for data collection. The REFA 128 model measures multiple monopolar EMG channels: up to 64 channels of monopolar EMG data were collected with Ag/AgCl electrodes in this experiment.

Electrode Placement

For normally limbed subjects 64 electrodes were placed on the forearm in an eight by eight grid formation. The circumference of a participants forearm was measured at the apex and at a position 14cm distal to the apex. These circumference measurements were divided by eight to determine the inter-electrode distance around the arm at the two points. The distance between the proximal and distal points were measured on both the anterior and posterior surface to ensure the lines of the grid formation do not drift. Eight electrodes were placed down the length of the forearm with an inter-electrode distance of 2cm. The first electrode was placed in the center of the anterior forearm at the apex. Electrodes two to eight were placed down the length of the forearm in line with electrode one. The first eight electrodes comprised row number one. The second row of electrodes was placed medially to the first row starting at the apex again and moving distally. The number of electrodes for transradial amputee subjects varied depending on the length of the residual limb (see Table 2.).

Testing Protocol

Normally limbed subjects performed 20 repetitions of up to 12 different hand and wrist movements. Each contraction was held for five seconds with a five second rest between each repetition. The 12 movements included six wrist movements: flexion, extension, pronation, supination, abduction, adduction, and six hand grips: hand open, chuck grip, key grip, power grip, fine pinch grip, and tool grip. After familiarization with each movement, subjects were asked to produce each contraction for a given movement as consistently as possible. Three of the normally limbed subjects (NL1, NL2, NL3) performed the contractions in randomized order for a series of trials. The other three normally limbed subjects performed all 20 repetitions of each movement together (two trails of ten contractions).

The testing protocol for transradial amputee subjects also varied from subject to subject (See Table 2). After the electrodes were applied the subjects were introduced to the movements and given time to practice performing different contractions. All amputee subjects were instructed to perform contralateral contractions when imagining performing different movements.

The first congenital amputee, CG1, was given a familiarization period where she was instructed to imagine performing different contractions. After practicing each motion the subject completed 10 repetitions of the 12 different wrist and hand movements.

The second congenital amputee, CG2, also had a familiarization period to practice imagining the different movements. This subject was then asked to identify which two of the hand grips were the easiest for him to imagine performing. They were fine pinch grip and power grip. These two hand grips along with hand open and the six wrist movements were then tested. The subject had difficulty imagining the contractions so he determined when to start each five second contraction. Ten, five second repetitions for each of the nine movements were completed.

The traumatic amputee had a familiarization period where she practiced the movements and identified the two hand grips she felt easiest to imagine. They were power grip and tool grip. These two movements along with hand open and the six wrist movements were then tested. The subject performed 20 repetitions (two trials of ten) of each of the nine movements.

Table 2: Transradial Amputee Subject Variations: Electrode placement, movements performed, and number of repetitions.

Subject	**Electrode Grid**	**Movements Performed**	**Repetitions**
CG1	8 x 2 (16 electrodes)	6 wrist motions, 6 hand grips, and no motion.	10 repetitions of each motion.
CG2	8 x 4 (32 electrodes)	6 wrist motions, hand open, pinch grip, power grip and no motion.	10 repetitions of each motion.
TR1	8 x 3 (24 electrodes)	6 wrist motions, hand open, power grip, tool grip, and no motion.	20 repetitions (2 trials of 10) of each motion.

Data Analysis

The Root Mean Square (RMS) of the monopolar EMG amplitude data collected from the HD sEMG system during each motion was used to create EMG energy maps. The maps indicate the areas of the forearm where muscle activity was detected during each movement. The average RMS of the amplitude data from all repetitions of each motion was used to generate energy maps. The energy maps were analyzed to investigate if repeatable and distinguishable muscle activation patterns were produced.

Pattern recognition was also performed on the HD sEMG data to confirm that distinguishable and reproducible muscle activation patterns were produced. The pattern classifier involved time domain features and a linear discriminant classifier as described in Englehart and Hudgins (2003). High classification accuracies verify the results and indicate the potential to control multifunction myoelectric prosthetic devices.

RESULTS

Within subject analysis was performed to determine the variance in EMG activity patterns across repetitions of each movement and across various movements. To determine if muscle activity patterns across different movements are distinguishable, pattern recognition was performed. Analysis was initially performed on all movements but some movements were omitted if the classification accuracy was poor.

Table 3: Classification Accuracies for Movements Performed by Normally Limbed and Transradial Amputee Subjects.

Subject	Number of Movements	Movements Included	Classification Accuracy
NL1	9	Pronation, Supination, Flexion, Extension, Hand Open, Key Grip, Power Grip, Fine Pinch Grip, No Movement	90.69%
NL2	11	Pronation, Supination, Flexion, Extension, Abduction, Adduction, Hand Open, Key Grip, Power Grip, Tool Grip, No Movement.	93.14%
NL3	5	Supination, Extension, Abduction, Tool Grip, No Movement.	88.9%
NL4	8	Supination, Flexion, Extension, Abduction, Adduction, Power Grip, Fine Pinch Grip, No Movement	89.61%
NL5	9	Flexion, Extension, Pronation, Supination, Abduction, Adduction, Key Grip, Chuck Grip, No Movement	92.79%
NL6	8	Supination, Flexion, Extension, Adduction, Hand Open, Power Grip, Chuck Grip, No Movement	89.94%
CG1	6	Pronation, Abduction, Key Grip, Power Grip, Tool Grip, No Movement.	86.01%
CG2	5	Supination, Flexion, Abduction, Hand Open, No Movement	87.65%
TR1	6	Pronation, Flexion, Abduction, Power Grip, Tool Grip, No Movement.	94.5%

The classification accuracy was higher for normally limbed subjects for a larger number of movements. However, the transradial amputee subjects did obtain strong classification accuracies for a subset of the movements. Table three shows movements and the classification accuracy of those movements.

Congenital amputee subjects had difficulty imagining different movements with the missing limb. The traumatic amputee subject experienced phantom limb and therefore could easily visualize the missing limb. She had a greater ability to imagine performing different movements compared to the congenital amputee subjects.

The amplitude data collected from the HD EMG system was used to generate energy maps in Matlab. The energy maps are made so that rows one to eight progress from the left to the right side of the graph. The top of the graph represents the proximal forearm and the bottom of the graph represents the distal forearm.

Energy maps can be generated for each repetition of each different movement. The average amplitude data from multiple repetitions of a movement can also presented in an energy map. Maps can be visually analyzed to examine repeatability across a series of repetitions. Figures one and two are energy maps of data from two congenital amputee subjects. The maps represent EMG activity in the forearm during two repetitions of wrist abduction. The figures indicate that the muscle activity patterns from repetitions early in the trial are similar to the activity patterns of repetitions later in the trial. The figures also illustrate that muscle activity patterns for abduction are different for each subject. Both subjects show muscle activity in two sites.

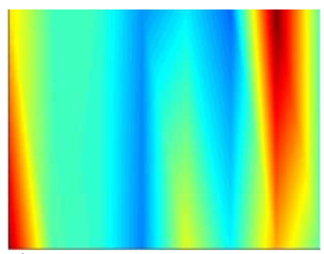

Figure 1a.

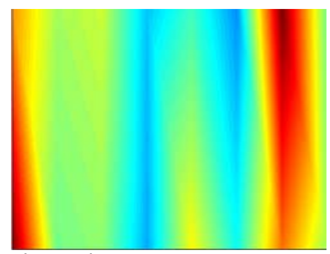

Figure 1b

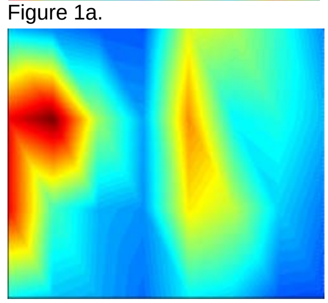

Figure 2a

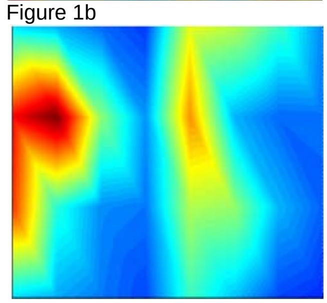

Figure 2b

Figures 1a and 2a show the average amplitude data from repetitions two and three of wrist abduction for subjects CG1and CG2 respectively. Figures 1b and 2b show the average amplitude data from repetitions eight and nine of wrist abduction for subjects CG1 and CG2 respectively.

The classification accuracies and the energy maps indicate that all subjects were able to produce distinguishable and repeatable muscle activation patterns for at least a subset of the different movements performed. The current data are from a small sample size, however further subject testing will be completed. Appropriate statistical analysis will be performed once a sufficient sample size is attained.

DISCUSSION

There has been a considerable amount of research advancing the technology of myoelectric prosthetic control. Over the last 50 years myoelectric control systems have developed from single muscle control of one prosthetic function to muscle group activity control of multiple prostheses functions (Parker et al. 2006). Progress in technology however has not been paralleled with research using clinical populations to test these new devices. Advanced systems have the ability to control multiple hand functions but they have yet to be applied in the clinical setting. Commercially available prosthetic devices are still only capable of controlling one or two degree of freedom (Englehart and Hudgins 2003).

Atkins et al. (1996) conducted a survey on upper limb amputees to identify what they considered the most important areas for improvement in prosthetic devices. The results form this study showed that amputees ranked additional movements of the prosthetic limb as a top priority for future improvements. This indicates a need to research and in turn improve clinical applications of multifunctional upper limb prosthetics.

Several studies have shown that normally limbed subjects are capable of producing distinguishable and repeatable muscle activation patterns for different movements (Hudgins et al. 1993). The same quantity of research efforts have not been made using amputees subjects. Some research has included amputee subjects (Hudgins et al. 1993, Lundborg 2000, Boostani and Moradi 2003, Fukuda et al. 2003, Sebelius et al. 2005, Ajiboye and Weir 2005, Sebelius et al. 2006) but further investigations of multifunction control are required. Therefore the purpose of this study was to determine if distinct and repeatable muscle activation patterns are produced by upper limb amputees during different wrist and hand movements. These patterns are essential for pattern recognition based myoelectric control and this work can be used to validate the well researched cases which use normally limbed subjects.

It was hypothesized that amputee subjects would produce different activation patterns compared to normally limbed subjects. Initial analysis of the amputee subjects energy maps indicate that differences do occur. Muscle activity patterns are unique to each amputee subject. Further statistical analysis with a larger sample will be conducted to confirm this finding.

It was also hypothesized that amputee subjects would be able to produce distinct and repeatable muscle activity patterns for at least a subset of the different movements performed. The strong classification accuracies support this hypothesis which suggests that amputee subjects are capable of controlling multifunction prosthetic devices. The energy maps also support the finding that muscle activity patterns are repeatable across repetitions.

The traumatic amputee showed stronger classification accuracies compared to the congenital amputee subjects. The traumatic amputee subject was able to easily visualize the missing limb and imagine performing different movements. The congenital amputees had a much harder time visualizing their missing limb. Imagining different movements with a limb they have never had was an abstract and difficult task which required a lot of concentration and effort.

CONCLUSION

These preliminary results are promising and indicate there is a future for multifunction pattern recognition based control systems in the clinical setting. Further testing is being conducted and additional analysis will be performed to confirm these results.

REFERENCES

Ajiboye, A. B., & Weir, R. F. (2005). A heuristic fuzzy logic approach to EMG pattern recognition for multifunctional prosthesis control. [Electronic version]. IEEE Transactions on Nerual Systems and Rehabilitation Engineering, 13(3), 280.

Englehart, K., & Hudgins, B. (2003). A robust, real-time control scheme for multifunction myoelectric control. IEEE Transactions on Biomedical Engineering, 50(7), 848-854.

Atkins, D. J., Heard, Denise C. Y., & Donovan, W. H. (1996). Epidemiologic overview of individuals with upper-limb loss and their reported research priorities. Journal of Prosthetics and Orthotics, 8(1), 2.

Boostani, R., & Moradi, M. H. (2003). Evaluation of the forearm EMG signla features for the control of a prosthetic hand. Physological Measurement, 24, 309-319.

Fukuda, O., Tsuji, T., Kaneko, M., & Otsuka, A. (2003). A human-assisting manipulator teleoperated by EMG signals and arm motion. IEEE Trans. on Robitics & Automation, 19(2), 210-222.

Hudgins, B., Parker, P., & Scott, R. N. (1993). A new strategy for multifunction myoelectric control. [Electronic version]. IEEE Transactions on Biomedical Engineering, 40(1), 82.

Lundborg, G. (2000). Tommorow's artificial hand. [Electronic version]. Scand J Plast Reconstr Hand Surg, 34, 97.

Parker, P. A., Englehart, K., & Hudgins, B. (2006). Myoelectric signal processing for control of powered prostheses. Journal of Electromyography and Kinesiology, 16(541), 548.

Sebelius, F., Eriksson, L., Blalkenius, C., & Laurell, T. (2006). Myoelectric control of a computer animated hand: A new concept based on the combine use of a tree-structured artificial neural network and a data glove. [Electronic version]. Journal of Medical Engineering & Technology, 30(1), 2.

Sebelius, Frederik C. P., Rosen, B., N., & Lundborg, G. N. (2005). Refined myoelectric control in below-elbow amputees using artificial neural networks and a data glove. [Electronic version]. The Journal of Hand Surgery, 30A(4), 780.