From "MEC 11 Raising the Standard," Proceedings of the 2011 MyoElectric Controls/Powered Prosthetics Symposium Fredericton, New Brunswick, Canada: August 14-19, 2011. Copyright University of New Brunswick.

PROSTHESIS-GUIDED TRAINING INCREASES FUNCTIONAL WEAR TIME AND IMPROVES TOLERANCE TO MALFUNCTIONING INPUTS OF PATTERN RECOGNITION–CONTROLLED PROSTHESES

Ann M. Simon[1*], Blair A. Lock[1], Kathy A. Stubblefield[1], and Levi J. Hargrove[1,2]
[1]Center for Bionic Medicine, Rehabilitation Institute of Chicago, Chicago, Illinois, USA
[2]Department of Physical Medicine and Rehabilitation, Northwestern University, Chicago, Illinois, USA
[*]Corresponding Author: asimon@ric.org

ABSTRACT

A remaining barrier to the clinical accessibility of pattern recognition systems is the lack of practical methods to acquire the myoelectric signals required to train the system. Many current methods involve screen-guided training (SGT), where wearers connected to an external computer perform muscle contractions synchronized with a sequence of visual cues. The system complexity prevents easy retraining when signal conditions change. We have developed a method called prosthesis-guided training (PGT), where the prosthesis itself provides the cues by moving through a sequence of preprogrammed motions; screen prompting and external connections are eliminated. Five prosthesis wearers performed a repetitive clothespin placement task using pattern recognition control. Wearers demonstrated similar baseline functionality between systems trained with PGT (10 ± 4 clothespins) and SGT (12 ± 7 clothespins) ($p = 0.56$). To investigate the efficacy of PGT retraining, real-world issues (e.g. broken wires, external noise) were simulated to accelerate control degradation. Sessions ended when wearers indicated loss of functional control. On average, wearers maintained function through two malfunctioning inputs, placing 48 ± 17 clothespins in 31.6 ± 16.2 minutes when allowed to retrain using PGT. These results suggest that PGT acquires adequate training data and may enable longer-lasting functional use, potentially increasing prosthesis wear time and reducing device rejection.

INTRODUCTION

Pattern recognition–based control has shown promise for myoelectric control of upper limb prostheses but has had limited clinical implementation. For pattern recognition systems to progress and move outside the laboratory, a few remaining barriers need to be addressed. This paper focuses on developing a practical way for prosthesis wearers to train the system.

Existing methods of acquiring the myoelectric signals necessary to train the system have generally relied on visual or auditory cues. During a screen-guided training (SGT) session, wearers connect to an external computer and perform muscle contractions synchronized with a sequence of visual cues [1]. This method has seen wide-spread implementation in the laboratory but may not be practical for home use. The requirement for an external display adds to system complexity and prevents easy retraining when signal conditions change. Auditory cues can eliminate the need for an external display but rely on the wearer to remember a preprogrammed sequence of movements.

Prosthesis-guided training (PGT) is a new method that eliminates the need for an external connection. During PGT, the prosthesis provides the cues for the wearer. Wearers initiate PGT by simply pushing a button. The prosthesis then moves itself through a sequence of preprogrammed motions. Wearers follow along with the prosthesis motions by performing the necessary muscle contractions and relaxing each time the prosthesis pauses between motions. The myoelectric signals that are collected during this sequence are immediately used to train and recalibrate the pattern recognition control system.

The goal of this study was to investigate the efficacy of retraining a pattern recognition prosthesis system using PGT, Wearers can encounter several different types of issues in their home and community that can cause their prosthesis control to degrade. Faulty electrodes and changes in signal quality are two major problems that can occur during use. We simulated these real-world issues at regular intervals in the laboratory to test wearer performance during periods of accelerated control degradation. Providing wearers with an easy method of retraining and recalibrating their prosthesis if and when these issues arise can increase wear time and reduce device rejection.

METHODS

Five individuals who had undergone TMR surgery participated in this study: two male participants with a right shoulder-disarticulation (S1 and S2), one female participant with a left shoulder-disarticulation (S3), one male participant with a right transhumeral amputation (T4), and one female participant with a left transhumeral amputation

(T5). All individuals used a myoelectric prosthesis and had experience with pattern recognition systems Participants gave written informed consent to participate in this study.

Eight bipolar electrode pairs were placed on the skin surface over the reinnervated muscles. The myoelectric signals were amplified, sampled at a frequency of 1 kHz, high pass filtered (20 Hz cutoff frequency) to reduce motion artifact, and processed in real time using custom software.

The pattern recognition algorithm was trained to recognize nine motions: elbow flexion, elbow extension, forearm supination, forearm pronation, wrist flexion, wrist extension, hand open, hand close, and no movement. Six seconds of data for each motion were used to train a linear discriminate analysis (LDA) classifier [2] and six seconds of data for each motion were used to determine the classification error. The EMG data were segmented into a series of 250 ms analysis windows [3] with a 50 ms window increment.

Four time-domain values (mean absolute value, number of zero crossings, waveform length, and number of slope size changes [4]) and autoregressive coefficients were computed and used in pattern classification. After the LDA classifier was trained, it was used to predict user commands and control a prosthetic arm. The motion speed was normalized to the training data contraction intensity and a 500 ms velocity ramp was applied to minimize the effect of misclassifications [5]. This setup resulted in a clinically viable, functional system requiring no experimenter adjustments of output gains or thresholds.

Prosthesis-Guided Training vs. Screen-Guided Training

Individuals participated in two separate experimental sessions. The difference between sessions was how the myoelectric signals required to train the pattern recognition system were collected. The order of sessions was randomized. For the SGT session, wearers were connected to an external computer and performed muscle contractions synchronized with a sequence of visual cues. For the PGT session, wearers performed muscle contractions synchronized with a sequence of preprogrammed motions of their prosthesis. Wearers self-initiated PGT by pushing a button attached to their prosthesis. Both methods collected the same amount of training data.

To measure performance between the two methods of collecting training data, wearers performed a repetitive clothespin placement task. In a 4 min baseline trial they moved as many clothespins as possible from a horizontal bar to a vertical bar [6] (Figure 1). A paired t-test was used to detect significant differences in performance between the two sessions.

Figure 1: Prosthesis wearer performing the clothespin placement task.

Accelerated Life Cycle Test

To investigate the efficacy of retraining the pattern recognition system using PGT, real-world issues were simulated to accelerate control degradation. The simulated real-world issues were either a faulty electrode or a noisy electrode. The simulated faulty electrode (i.e. channel amplitude set to zero) was representative of a broken wire or faults in the electrode circuitry. The simulated noisy electrode (i.e. addition of large 60 Hz interference) was representative of external noise and/or electrode lift-off. Issues were cumulative in nature and wearers were blind to the type and timing. Wearers performed the repetitive clothespin placement task in 12 min blocks, each followed by a 4 min break. Four minutes into each block, one issue was applied to a randomly selected channel. Wearers were instructed to continuously perform the clothespin task. Sessions ended when wearers were no longer able to place clothespins, indicating a loss of functional control.

During the PGT session, wearers were able to self-initiate recalibration of their prosthesis when they believed their performance had degraded. During the separate SGT session, wearers did not have the option to recalibrate their prosthesis. This session was representative of the wearer being in an environment where the external computer necessary for SGT was not available. The simulated electrode issues occurred in the same order across sessions and the order of sessions was randomized. Performance metrics included prosthesis wear time, total number of clothespins placed, number of issues overcome, and the times between onset of an issue and initiation of retraining using PGT.

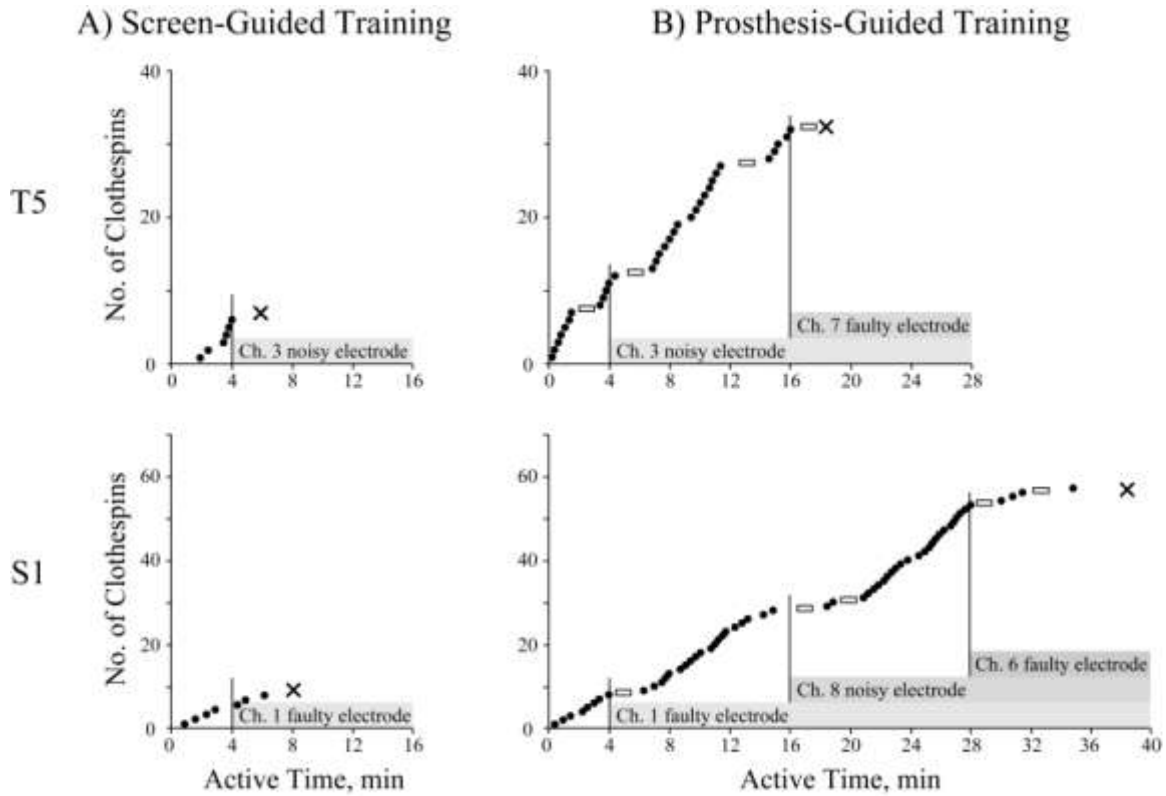

Figure 2: Number of clothespins placed vs. time for a prosthesis wearer with a shoulder disarticulation (S1) and a prosthesis wearer with a transhumeral amputation (T5) for (A) screen-guided and (B) prosthesis-guided training. The active time reported does not include the 4 min breaks that occurred every 12 min. The simulated real-world issues were cumulative in nature. Circles indicate a successfully placed clothespin, rectangles indicate self-initiated PGT (if available), and x indicates loss of functional control.

RESULTS

Prosthesis-Guided Training vs. Screen-Guided Training

Classification error for myoelectric signals collected during SGT (7.8% ± 3.5%) (mean ± standard deviation) was significantly lower than during PGT (18.1% ± 2.8%) (paired t-test, p = 0.009). During the baseline clothespin test, wearers demonstrated similar baseline functionality between systems trained with SGT (12 ± 7 clothespins) and PGT (10 ± 4 clothespins) (p = 0.56).

Accelerated Life Cycle Test

Figure 2 shows the accelerated life cycle test for two wearers. In this example, an individual with a transhumeral amputation (T5) lost functional control after one channel was affected. With SGT and no option to recalibrate her prosthesis, her only option was to take the prosthesis off (Figure 4A). With PGT available, she recalibrated her prosthesis when her control degraded. She maintained function after the same channel was affected, thereby extending the functional use time of her prosthesis (Figure 4B). An individual with a shoulder disarticulation (S1) also lost functional control a few minutes after one myoelectric channel was affected. With the option to retrain using PGT, he was able to maintain function even after three of eight myoelectric signals were affected (two channels had simulated faulty electrodes and one channel had simulated noise). This individual retrained his prosthesis using PGT five times. When pattern recognition control degraded in response to simulating either faulty electrodes or noisy electrodes, all wearers initially chose to retrain their prosthesis instead of indicating loss of functional control and taking their prosthesis off.

During the SGT session with no external computer available to recalibrate their prosthesis, wearers placed a average of 10 ± 5 clothespins in 6.2 ± 1.7 minutes. Given the option to retrain their prosthesis using PGT, wearers placed an average of 48 ± 17 clothespins in 31.6 ± 16.2 min. With PGT, wearers maintained function through an average of 2.0 ± 1.4 malfunctioning input channels. After a signal channel was affected, wearers retrained their prosthesis using PGT within 32 ± 22 seconds. Wearers retrained their prosthesis an average of 5.8 ± 4.1 times.

One wearer (T4) was excluded from the analysis because his results were constituted as an outlier; his performance metrics for both SGT and PGT sessions were above the sum of the third quartile and 1.5 times the interquartile range. T4 did, however, show the same trend that he was able to overcome malfunctioning input channels and extend functional use when allowed to retrain using PGT. He placed 57 clothespins in 15.8 minutes during the SGT session and 104 clothespins in 42.5 minutes during the PGT session.

DISCUSSION

Results from the baseline clothespin test demonstrate similar functionality between systems trained with SGT and PGT. The myoelectric signals collected during PGT may be different than those collected during SGT. During SGT, wearers are focused on a display while performing the muscle contractions and their prosthesis remains static in the neutral position. During PGT, wearers, by design, are focused on their prosthesis. Their prosthesis is in motion, providing the cues necessary for them to initiate the corresponding muscle contractions. As the prosthesis moves, it alters socket-tissue loading and the muscle activity necessary to support the moving weight. Therefore the conditions in which these signals are collected in order to train the pattern recognition system are more similar to the environment in which wearers will use their prosthesis. These changes are recorded during PGT but not SGT. PGT may capture more transient signals as each muscle contraction is recorded from rest, which may have lead to the higher PGT error rates during offline analysis [7].

Our results suggest that with PGT, wearers may be willing and able to maintain functional use of their prosthesis longer than without it. When we simulated a broken wire or signal noise, wearers noticed their control degrade. With SGT and no external computer available, wearers lost functional control and had no other choice but to take their prosthesis off. SGT does not necessarily require an external computer and could be performed using a smartphone application. Nonetheless, equipment in addition to the prosthesis is still required and smartphones may not be available to or desirable for all wearers.

With PGT, wearers self-initiated recalibration of their prosthesis in an attempt to restore control within an average of 30 s. If they were at home and a wire broke, PGT may provide them with a longer time frame of functional use before they need to go back to the clinic. Without PGT, most likely the device would be uncontrollable. Wearers would not have the option of using their prosthesis until they could return to the clinic. For less extreme issues, such as changes in skin conditions or muscle fatigue, PGT would also offer wearers the ability to quickly recalibrate their control.

CONCLUSIONS

PGT is a straightforward way for wearers to retrain and recalibrate their prosthesis when myoelectric signal conditions change. With PGT, wearers can take an active role in trying to improve their control and attempt to overcome control issues instead of taking their prosthesis off. This study demonstrated that wearers are willing and able to retrain their prosthesis. Wearers can seamlessly transition back to the task they were performing prior to the PGT session. This new method of acquiring the myoelectric signals necessary to train a pattern recognition system has the potential to increase wearers' usage time and reduce device rejection.

REFERENCES

[1] T.A. Kuiken, *et al.*, "Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms," *JAMA*, vol. 301, pp. 619-28, Feb 11 2009.

[2] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans Biomed Eng,* vol. 50, pp. 848-54, Jul 2003.

[3] L.H. Smith, L.J. Hargrove, B.A. Lock, and T.A. Kuiken, "Determining the Optimal Window Length for Pattern Recognition-Based Myoelectric Control: Balancing the Competing Effects of Classification Error and Controller Delay," *IEEE Trans Neural Syst Rehabil Eng,* vol. 19, pp. 186-92, 2011.

[4] B. Hudgins, P. Parker, and R.N. Scott, "A new strategy for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering,* vol. 40, pp. 82-94, Jan 1993.

[5] A.M. Simon, L.J. Hargrove, B.A. Lock, and T.A. Kuiken, "A strategy for minimizing the effect of misclassifications during real time pattern recognition myoelectric control," *Conf Proc IEEE Eng Med Biol Soc,* vol. 2009, pp. 1327-30, 2009.

[6] L.A. Miller, K. Stubblefield, R. Lipschutz, B.A. Lock, and T.A. Kuiken, "Improved myoelectric prosthesis control using targeted reinnervation surgery: a case series," *IEEE Trans Neural Syst Rehabil Eng,* vol. 16, pp. 46-50, Feb 2008.

[7] L.J. Hargrove, Y. Losier, B.A. Lock, K. Englehart, and B. Hudgins, "A real-time pattern recognition based myoelectric control usability study implemented in a virtual environment," *Conf Proc IEEE Eng Med Biol Soc,* pp. 4842-5, 2007.