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Prosthesis-Guided Training of Pattern Recognition-Controlled Myoelectric Prosthesis

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Abstract— **Pattern recognition can provide intuitive control of myoelectric prostheses. Currently, screen-guided training (SGT), in which individuals perform specific muscle contractions in sync with prompts displayed on a screen, is the common method of collecting the electromyography (EMG) data necessary to train a pattern recognition classifier. Prosthesis-guided training (PGT) is a new data collection method that requires no additional hardware and allows the individuals to keep their focus on the prosthesis itself. The movement of the prosthesis provides the cues of when to perform the muscle contractions. This study compared the training data obtained from SGT and PGT and evaluated user performance after training pattern recognition classifiers with each method. Although the inclusion of transient EMG signal in PGT data led to decreased accuracy of the classifier, subjects completed a performance task faster than when compared to using a classifier built from SGT data. This may indicate that training data collected using PGT that includes both steady state and transient EMG signals generates a classifier that more accurately reflects muscle activity during real-time use of a pattern recognition-controlled myoelectric prosthesis.**

I. Introduction

Pattern recognition is an intuitive control technique for upper limb myoelectric prostheses, as it predicts an individual's intended movement by decoding their muscle signals. In order to train a pattern recognition-controlled prosthesis, myoelectric signals representative of each movement of the prosthesis must first be collected [1]. Typically this has been done through use of screen-guided training (SGT). Individuals are prompted to perform specific movements using images displayed on a screen, and the corresponding electromyography (EMG) data is sampled [2,3,4]. This data collection method requires the ability to connect to a display. Screen prompts allow for customization of the information displayed to individuals; however, they also require patients to make a cognitive transformation between the two-dimensional prompt and the movement of their residual limb. SGT can be used to train a pattern recognition system even if a socket and prosthesis are not currently available. If the individual is wearing the prosthesis, it remains still throughout SGT.

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Prosthesis-guided training (PGT) is a new way to collect the myoelectric signals necessary to train a pattern recognition system during which individuals are prompted by the movement of the prosthesis itself [5]. The prosthesis moves one degree-of-freedom at a time and users follow along with these movements as EMG data is sampled. For example, once PGT is initiated, the prosthesis actuates one degree-of-freedom, say the elbow. As the prosthesis is driven into elbow flexion, the individual performs a similar elbow flexion muscle contraction; when the prosthesis stops moving, the individual relaxes. Then the prosthesis is driven into elbow extension and the individual similarly follows along by performing an elbow extension muscle contraction. PGT continues actuating each individual degree-of-freedom with the prosthesis user contracting his or her muscles for each respective movement of the prosthesis, always relaxing their muscles when the device is at rest. Users know that PGT is complete after all movements have been performed and the prosthesis remains at rest. The pattern recognition classifier is quickly built and the individual can immediately begin controlling the prosthesis. The entire process takes about one minute for a four degree-of-freedom system.

One advantage of PGT is that it requires no additional hardware and can be initiated simply with the press of a button. Individuals would be capable of training their pattern recognition-controlled prosthesis anywhere in their home or community. This training method provides users with a real-time demonstration of each movement to be performed and keeps the individuals' focus on the prosthesis, where it will be during actual use. Thus PGT avoids the additional visuomotor transformation from a static visual cue to a dynamic motor output.

During PGT, the user is instructed to not anticipate prosthesis movements and contract their muscles only when the prosthesis moves. This ensures that both transient and steady state EMG data are collected. Inclusion of both transient and steady state data is thought to improve the robustness of the resulting classifier [6]. Custom algorithms separate the muscle contraction data from the rest data such that only muscle contraction data is used to train each movement class. Collecting data while the prosthesis is moving also ensures that EMG signal changes due to limb stabilization are recorded in the training data.

The goal of this study was to compare users' pattern recognition performance following SGT and PGT. We hypothesized that both training methods would collect

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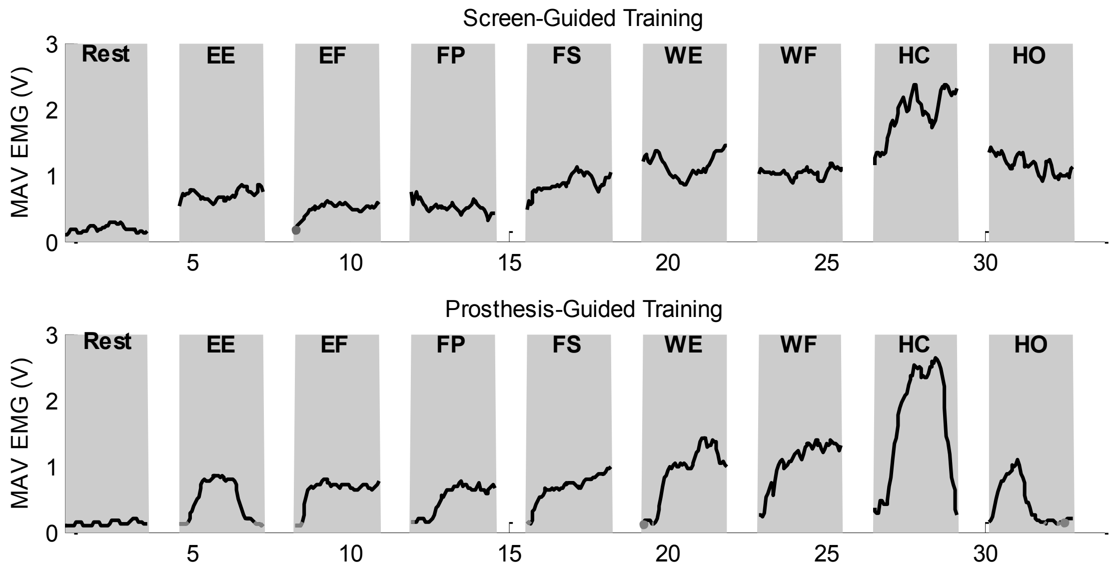

Figure 1. EMG mean absolute value, summed across all channels, for contractions that Participant S1 performed during one repetition of each movement class for SGT and PGT. EE, elbow extension; EF, elbow flexion; FP, forearm pronation; FS, forearm supination; WE, wrist extension; WF, wrist flexion; HC, hand close; and HO, hand open. Data points collected during a motion class but relabeled as rest data by the custom algorithm are shown in dark gray.

slightly different sets of data but that both would allow subjects to control the prosthesis.

II. Methods

A. Participants

Two individuals participated in this study: one male participant with bilateral shoulder disarticulations (S1) and one male participant with a right transhumeral amputation (S2). Both had undergone targeted muscle reinnervation (TMR) surgery, during which nerves that previously innervated muscles in the amputated limb are transferred to muscles that are no longer biomechanically functional, allowing their neural signals to be captured via surface EMG [7]. Participants had experience controlling pattern recognition-controlled systems and gave written informed consent.

B. EMG and Pattern Recognition Setup

Eight bipolar surface EMG electrodes were placed over the reinnervated muscle area. The EMG signals were amplified and high pass filtered with a cutoff frequency of 80 Hz for Participant S1 to remove ECG artifact [8], and 20 Hz for Participant S2. Data was sampled at a frequency of 1 kHz and processed in real-time using custom software [9].

Subjects trained the pattern recognition classifier to recognize nine classes: elbow flexion, elbow extension, forearm supination, forearm pronation, wrist flexion, wrist extension, hand open, hand close, and rest. Training data was collected using either screen-guided or prosthesis-guided training. During SGT, subjects began each muscle contraction when prompted by the visual display. During PGT, subjects began each muscle contraction when the prosthesis began making the corresponding movement. For both data collection methods, subjects were instructed to perform the movements at a comfortable level of effort. Six seconds of data per class were used to train a linear discriminant analysis (LDA) classifier, and six seconds of data per class were used to test the classifier.

The EMG data from each channel were segmented into 250 ms analysis windows with a 50 ms frame increment. A threshold based on the level of myoelectric activity recorded during rest was used to segment the muscle contraction data [5, 10]. Any data recorded during a motion class below the threshold of 1.1 times the average mean absolute value (MAV) during rest were relabeled as rest data prior to building the classifier. This thresholding ensured that only data during active muscle contractions were used for training each motion class; a larger lag between when the prosthesis began its actuation and when the individual started to perform his or her muscle contractions resulted in more rest class data (Fig. 1). Four time-domain features (MAV, wave vertical length, number of zero crossings, and number of slope changes) and sixth order autoregressive coefficients [11] were extracted from the EMG data. The resulting LDA classifier was used to control a prosthesis with the four trained degrees of freedom. A 500 ms velocity ramp minimized the impact of real-time classification errors by decreasing the initial speed of the prosthesis each time it changed motions [2].

C. Performance Evaluations

Offline classification error was calculated for SGT and PGT to assess the separability and repeatability of the data collected with each method. Accuracy was also calculated between training methods (i.e., trained with SGT and tested with PGT and vice versa) to compare the content of the data obtained from the two methods. These calculations were done for classifiers built from the transient and steady

TABLE I. CONFUSION MATRIX FOR S1, DATA TRAINED WITH SGT AND TESTED WITH PGT

Prompted Motion	**Predicted Motion**								
	Rest	***EF***	***EE***	***FS***	***FP***	***WF***	***WE***	***HO***	***HC***
Rest	83	5			12				
EF	2	98							
EE	11	4	82		2		1		
FS	2	4		91	4				
FP	5	1	1		92	1			
WF		8		5	17	69			
WE	1	8		6	4		81		
HO	15	21	2		33			29	
HC	2	18		1	36	3		3	36

TABLE II. CONFUSION MATRIX FOR S1, DATA TRAINED WITH PGT AND TESTED WITH SGT

Prompted Motion	**Predicted Motion**								
	Rest	***EF***	***EE***	***FS***	***FP***	***WF***	***WE***	***HO***	***HC***
Rest	62				25			12	
EF	4	81			5			11	
EE	2		59		27			13	
FS				86	13				1
FP					98				2
WF					5	92		3	
WE				1	13		85	2	
HO								100	
HC						1			99

state EMG and only the steady state data in order to examine the impact of the transient EMG signal that is more frequently captured in prosthesis-guided training data.

Subjects performed a clothespin placement test [7] to measure the real-time controllability of the prosthesis. The test involved moving clothespins from a horizontal bar to a vertical bar and required use of the elbow, wrist, and hand. The time required to move three clothespins was recorded. The test was repeated until subjects completed three tests without dropping a clothespin.

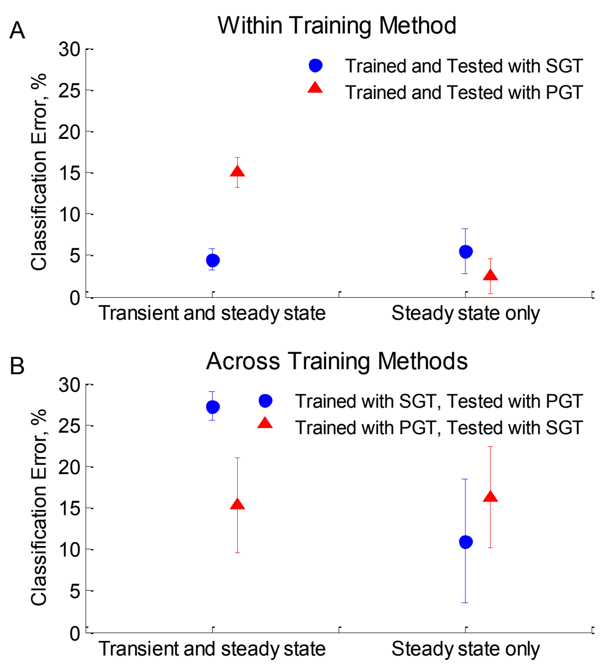

Figure 2. Average classification error calculated for classifiers trained and tested with data from A) the same training method and B) the opposite training method. Error bars are standard deviation.

Subjects completed these tests alternating between using SGT and PGT to train the prosthesis. Each method was tested three times. The first time was considered practice, and the second and third times were used for analysis.

III. Results

The EMG MAV from training data shows differences between the myoelectric activity collected during SGT and PGT (Fig. 1). SGT captures primarily sustained muscle contractions, whereas PGT often captures the onset and termination of the contractions in addition to the steady state movement.

Using the transient and steady state data to train the classifier, SGT resulted in fewer classification errors than PGT; however, using only the steady state data, SGT and PGT give similar levels of accuracy (Fig. 2A).

Using the transient and steady state data, classifiers trained with SGT and tested with PGT have higher error rates than those trained with PGT and tested with SGT. The corresponding confusion matrices are shown in Tables 1 and 2. However, using only the steady state data, these tests show a similar level of accuracy (Fig. 2B).

Subjects completed the clothespin test faster when PGT was used to train the classifier compared to SGT. For Participant S1, average completion time was 50.5 ± 10.3 s with SGT and 37.7 ± 5.4 s with PGT. For Participant S2, average completion time was 25.5 ± 5.8 s with SGT and 21.8 ± 2.6 s with PGT.

IV. Discussion

PGT captures the transient EMG without prompting the user with a count-down of the next actuated motion. The lag between the initiation of actuated prosthesis movement and the initiation of the individual's corresponding muscle contraction likely does not adversely affect the classifier's performance. The data collected during this time is below the myoelectric activity threshold and thus is relabeled and used in the rest class data set. Similarly, any data collected after the prosthesis stops moving and the individual relaxes is relabeled and used in the rest class. While this method of thresholding was applied to separate the data collected during PGT, it was also applied, for consistency, to SGT data.

The inclusion of transient EMG signals in PGT data is a main contributor to the observed differences in classification accuracy. When looking at classifiers built and tested within a training method, pattern recognition classifiers built from SGT data or only the steady state portion of PGT data have similar levels of error (Fig. 2A). Classifiers built using the transient and steady state data recorded from PGT (the only data set to include a large amount of transient signals) show higher error rates. Hudgins [10] found that transient EMG signals were highly separable and contained deterministic information; however, a buffer of 256 ms was used to interpret the transient signal. It is possible that the sliding window approach used to make continuous classification is not linearly separable until a sufficient amount of transient data has entered the buffer. This is consistent with the finding in this study that the PGT-based classifiers had lower offline classification accuracies than those generated from SGT data. Modifications to the pattern recognition classifier, such as incorporation of a similar buffer or use of an alternative to the LDA classifier, may be explored in future efforts to enhance PGT performance.

Despite lower classification accuracies, subjects perform as well or better when using the prosthesis trained with PGT. While subjects were able to use their prosthesis trained from SGT, PGT most likely captures a wider range of data during training. This is evident in our results that pattern recognition classifiers trained with PGT data and tested against SGT data yield fewer errors than those trained with SGT data and tested against PGT data. Using the transient as well as the steady state EMG to build a classifier can result in a pattern recognition system with fewer differences between training and real-time use. During use, individuals must perform a series of muscle contractions in order to perform a task with their prosthesis and those muscle contractions will most likely have more transient EMG than steady state. Hargrove et al. similarly observed that inclusion of transient signals led to lower accuracies but improved performance by healthy subjects on a virtual clothespin task [6].

The hand open and close degree-of-freedom provides a good illustration of including the transient EMG in the training data set. Compared with the elbow and wrist, the prosthetic hand used during this study had the smallest range of motion. While collecting data with PGT, the hand only took 1 s to fully open or close instead of the full 3 s as was the case for the elbow and wrist range of motion. Since individuals timed their contractions to the movement of the prosthesis, their hand open and hand close muscle contractions contained a proportionally higher amount of transient EMG than the other motion classes (Fig. 1). The greater amount of transient corresponds to the inability of a classifier trained with SGT data, which lacks the transient information, to correctly classify hand open and close data collected using PGT. Table 1 shows accuracies of 29% and 36% for these classes, respectively. However, with only a small amount of steady state hand open and close data that was recorded during PGT, the PGT-based classifier achieves accuracies of 100% and 99% for hand open and close, respectively, when tested with SGT data (Table 2).

V. Conclusions

PGT could serve as a valuable method of collecting training data for pattern recognition systems in both research and clinical settings. It allows individuals to easily train or retrain their pattern recognition-controlled myoelectric device without additional equipment. Further testing is needed to see if similar results are found for a greater number of amputees with a range of experience levels, different levels of amputation, and those individuals who have not had TMR surgery.

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