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Improving Myoelectric Pattern Recognition Positional Robustness Using Advanced Training Protocols

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Abstract - The control of powered upper limb prostheses using the surface electromyogram (EMG) is an important clinical option for amputees. There have been considerable recent improvements in prosthetic hands, but these currently lack a control scheme that can decode movement intent from the EMG to exploit their mechanical dexterity. Pattern recognition based control has the potential to decode many classes of movement intent, but is confounded when using the prosthesis in varying positions during activities of daily living. This work describes the degradation that can occur when using pattern recognition in varying positions, during both static positioning tasks and dynamic activities of daily living. It is shown that training with dynamic activities can greatly improve positional robustness for both static and dynamic tasks, without requiring a complex and lengthy training session.

I. Introduction

Powered upper limb prostheses controlled using the surface electromyogram (EMG) have been available for many decades, allowing autonomous control of limb positioning and hand manipulation. The required muscular contractions are often similar to those needed to articulate an intact limb. Although it has been found that myoelectric prostheses can be clinically practical in upper limb prosthetics, the limited dexterity of control is often cited as the primary reason for rather low acceptance of these devices [1].

Conventional myoelectric control schemes use an amplitude measure at each electrode site (such as the root mean square or mean absolute value of the EMG) to quantify the intensity of contraction in the underlying muscles. Control is elicited by mapping this activity to the desired prosthetic function. If more than one device is to be used, mode switching is often the only strategy, using a hardware switch or co-contraction to direct control to an elbow, wrist or hand. This method of control is often slow and counterintuitive [2].

This has motivated the use of a pattern recognition approach to myoelectric control. By using multiple EMG sites, effective feature extraction and multidimensional classifiers, it is possible to discriminate many more classes of motion than with conventional control. The use of EMG pattern recognition has been shown to greatly improve the dexterity of control in upper limb prostheses and, through the efforts of many academic and commercial initiatives, it is nearing clinical viability [3].

There are a number of factors that currently challenge pattern recognition control in clinical settings, including variation in electrode placement [4,5] and impedance, and the effects of socket loading and limb position [6]. This work addresses the degradation caused by limb position during static and dynamic tasks, and describes an effective training strategy to minimize the effects.

II. Methodology

A. Experimental Protocol

EMG data corresponding to eight classes of motion were collected from five right-handed, healthy, normally-limbed subjects (4 male, 1 female). All experiments were approved by the University of New Brunswick's Research Ethics Board. The subjects were fitted with a cuff made of thermo formable gel (taken from a 6mm Alpha liner by Ohio Willow Wood) that was embedded with eight equally spaced pairs of stainless steel dome electrodes. The cuff was placed around the right forearm, proximal to the elbow, at the position with largest muscle bulk. A reference electrode was placed over the back of the hand.

The eight channels of EMG were differentially amplified using remote AC electrode-amplifiers (BE328, by Liberating Technologies, Inc), and low pass filtered with a cutoff frequency of 500Hz. Finally, data were acquired using a 16 channel 16-bit analog-to-digital converter (USB1616FS from Measurement Computing^{TM}) sampling at 1kHz.

Subjects were prompted to elicit a *set* of contractions consisting of the following eight classes of motion: wrist flexion/extension, wrist pronation/supination, hand open, power grip, pinch grip, and a no motion (i.e. rest) class. Subjects were encouraged to perform contractions at a repeatable 'medium' force level and given rest periods between trials to minimize fatigue.

These sets were repeated during three sessions, each involving a different form of positional variation.

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Session 1: Static Positions

The eight motion classes were sustained while holding the arm in the following positions.

P_1: 'Neutral', arm hanging at side

P_2: 'Drinking', as if holding a cup up to one's mouth

P_3: 'Table Top', as if reaching for something ahead

P_4: 'Cupboard', as if reaching for something up high

P_5: 'Bending', as if picking something up from ground

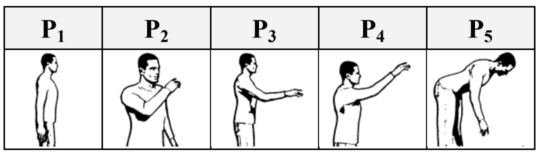

Figure 1: Static Limb Positions

Four sets of contractions were collected in each of the static positions. Contraction classes were held for 3 seconds, with 3 second inter-class delays. Two of these sets were used for training and two were used for testing.

Session 2: Activities of Daily Living

A more meaningful assessment of the usability of a control system is its accuracy while performing functional tasks: *activities of daily living* (ADL). The following ADLs were completed while holding each of the eight classes of motion:

A_1: P_3 to P_2 (Table Top to Drink)

A_2: P_1 to P_3 (Neutral to Table Top)

A_3: P_1 to P_4 (Neutral to Cupboard)

A_4: P_1 to P_5 (Neutral to Bending)

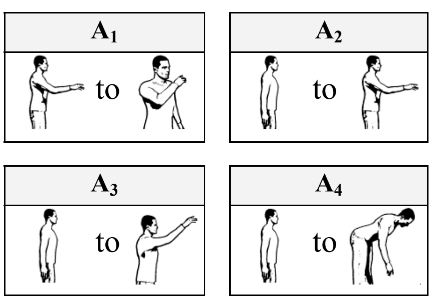

Figure 2: ADL Motions

Each ADL was repeated for 2 sets of motion classes. Each repetition took 4 seconds with a 3 second inter-motion delay. The difference in repetition length between the sessions was chosen so that the total amount of training data was similar for each method.

Session 3: Dynamic Training Motions

It was hypothesized that dynamic training data would be a more effective paradigm for training a system that would be used when performing ADLs. Rather than have the users perform the ADLs explicitly, two generic dynamic motions were defined that would encompass the positional variation experienced during ADLs. The motivation for this was to simplify the training process. Executing all eight motions during each ADL would be time-consuming; having only one or two dynamic trials would take much less time. These dynamic training motions were:

D_1: Humeral rotation starting in P_2

D_2: P_1, P_5, P_4, P_1 (as if picking up something from the floor and lifting it to a cupboard)

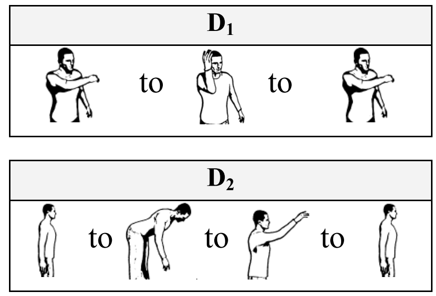

Figure 3: Dynamic Training Motions

For each of these dynamic training motions, two sets of contractions with 8 second repetitions and 3 second inter-repetition delays were collected.

B. Data Processing

In order to maintain a clinical focus, a control scheme similar to the one described by Englehart and Hudgins [7] was used. They showed that a simple time-domain (TD) feature extraction combined with a linear discriminant analysis (LDA) classifier could be used as an effective real-time control scheme for myoelectric control. Because of its relative ease of implementation and high performance, this system has been widely accepted in the research community, and is beginning to gain traction in clinical settings [8].

EMG data were notch filtered at 60Hz using a 3rd order Butterworth filter in order to remove any power line interference. Data were segmented for feature extraction using 200ms windows, with processing increments of 50ms.

III. Results

A. Static Training Results

Almost without exception, the approach to pattern recognition control has been to train with statically-held contractions. Nominally, these static contractions have been performed in a neutral position. When training in static positions, the effect of varying position has been shown to degrade accuracy [6]. This experiment has replicated these results, and extended the inquiry to determine the effect of position when performing ADLs.

Figure 4 illustrates that when training and testing in the same static position, very good performance results, with classification error ranging between 2.2 % (P1: 'Neutral') and 5.5% (P3: 'Table Top'). The error degrades considerably in most cases when testing in a different position than the training set (looking off of the main diagonal). It is evident that pooling data from all positions in the training set (P_{ALL}) is very effective, resulting in even lower error than training in the appropriate position.

When testing with the ADL data, it is clear that static training performs poorly indicating that, even when pooling data from all positions, the static data is just not representative of the dynamic ADL data.

Static Training Position

Test Position / Motion						P_{ALL}
	2.2	10.9	6.2	6.0	3.8	1.6
	22.3	4.3	11.9	12.0	19.5	3.7
	9.1	9.4	5.2	7.1	7.2	2.0
	19.9	15.4	20.1	3.9	17.8	3.7
	3.7	11.9	6.0	6.0	3.5	1.9
A_1	28.4	15.2	19.9	16.9	26.9	12.1
A_2	22.7	24.5	21.0	17.5	26.7	14.8
A_3	28.1	25.6	27.6	20.5	29.3	18.2
A_4	11.8	20.1	13.9	12.5	13.6	8.6

Figure 4: Inter-position accuracy (percent) when training with static positions (P_{ALL} denotes training with all static positions pooled)

B. Dynamic Training Results

The same analysis was performed when using the dynamic training data. The results in Figure 5 demonstrate that the dynamic training data allow the static position data to be reasonably well classified, but hold a clear advantage over static training when classifying the ADLs.

The relative efficacy of static versus dynamic training can be seen more clearly if the results across all positions (P1-P5) are averaged, as shown in Figure 6. For the *static testing data* (blue), the average error is high when training in individual static positions, and low when pooling the static positions (2.6%). The dynamic training data performs reasonably well on the static data if both D_1 and D_2 are included (4.6%).

Dynamic Training Motion

Test Position / Motion	D_1	D_2	D_{1-2}
	10.9	5.0	3.5
	6.4	11.9	4.7
	8.2	6.7	4.3
	12.9	9.6	6.8
	9.7	4.4	3.9
A_1	12.2	12.2	7.7
A_2	18.0	10.1	8.6
A_3	17.2	7.9	7.9
A_4	16.6	6.1	5.5

Figure 5: Inter-Position/Motion error (percent) when training with dynamic motions and testing in static positions

When testing with the ADLs, it is clear that when training with the static position data, the results are very poor; even with the pooled static position data. When training with the dynamic data, the results are much better, particularly with D_2 and D_1-D_2.

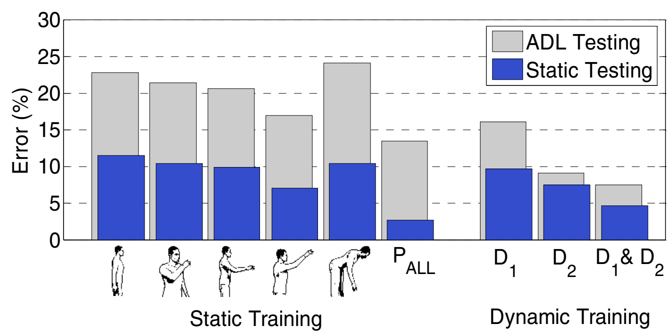

Figure 6: Comparison of all static and dynamic results

C. Examining the Dynamic Position Effect

The representation of EMG is in a high-dimensional feature space (eight channels x four features/channel = 32 features), and changes due to position are difficult to visualize. The feature that carries the most discriminant information is the mean absolute value (MAV), and therefore, one can simplify the observation of positional effects by looking at only this feature. Figure 7 depicts the MAV from each of eight EMG channels as a function of time (or excursion along the reaching motion A_3). Also shown are the classifier decisions when using static training in the neutral position (dashed) and with dynamic training (solid blue).

In Figure 7a, the subject is attempting to raise the arm while intending to elicit 'no motion' in the prosthesis. Beginning from a neutral position, the MAV on all channels is low, as would be expected when performing 'no motion,' but as the arm is raised, two channels experience a noticeable increase in MAV as the forearm muscles must stabilize the limb against gravity. With static training (from the neutral position), the classifier begins to erroneously classify the motion as wrist supination as the MAV increases. With dynamic training, no errors occur, as the classifier has been trained with 'no motion' data while the subject was actively positioning the limb.

Figure 7b shows the same scenario, while the subject attempted to extend the wrist while reaching. The MAV features from this active class are over the course of the reaching motion; the classifier trained on static data produces erratic results, while the classifier trained on dynamic data performs well until the final portion of the reaching motion.

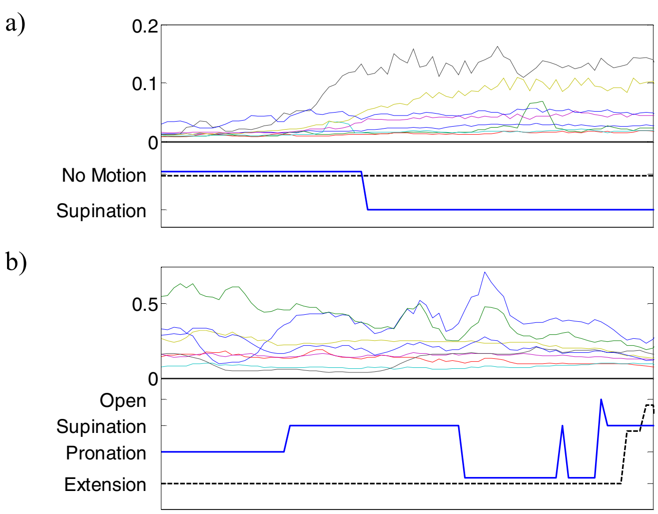

Figure 7: Example of MAV feature trajectories (top) during reaching motion A_3 and resulting class decisions (bottom) when training with static neutral position P_1 (solid line) with dynamic training motion D_2 (dashed line). The target classes were a) no motion, and b) wrist extension

IV. Discussion

These results demonstrate that the performance of a pattern recognition control system is greatly influenced by the position of the limb and whether the limb is still or moving while eliciting the desired movement intent.

If a prosthesis is to be controlled exclusively by producing EMG commands while holding the limb in the desired position, training with exemplars of the contractions in all desired positions works very well, as shown in Figure 6. This, however, imposes a rather extensive training session for the amputee. In our sessions, training in all positions requires about 10 minutes, which is tedious for the user.

Using a prosthesis in this manner is also unnatural in some cases. Many ADLs are more naturally performed when actively controlling the prosthesis while positioning, such as orienting the wrist while bringing a cup towards the mouth. Static training does not perform well when the goal is to control the prosthesis while performing ADLs. It has been shown that dynamic training is a much better approach. Training during a single dynamic motion (D_2) can produce very good results for both static positioning and ADL tasks; combining two dynamic motions (D_1 & D_2) performs slightly better. Training with a single dynamic task requires only 1-2 minutes.

The next stage of this investigation will involve amputee users, wearing powered prostheses. This will introduce a number of additional factors, including the variation in musculature, possibly altered motor pathways, socket loading and the inertia/vibration caused by powered components. Our goal is to establish best practices to provide control that is robust by incorporating meaningful variations into the training session.

Our experience is that a training session has poor resilience from day to day. That is, a system trained on one day may not perform well the next, likely due to electrode position and skin impedance. Consequently, it is important that the time and complexity of the training session is sufficiently low enough to be performed easily by the user on a daily basis.

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