Examining the Adverse Effects of Limb Position on Pattern Recognition Based Myoelectric Control

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***Abstract*—Pattern recognition of myoelectric signals for the control of prosthetic devices has been widely reported and debated. A large portion of the literature focuses on offline classification accuracy of pre-recorded signals. Historically, however, there has been a semantic gap between research findings and a clinically viable implementation. Recently, renewed focus on prosthetics research has pushed the field to provide more clinically relevant outcomes. One way to work towards this goal is to examine the differences between research and clinical results. The constrained nature in which offline training and test data is often collected compared to the dynamic nature of prosthetic use is just one example. In this work, we demonstrate that variations in limb position after training can have a substantial impact on the robustness of myoelectric pattern recognition.**

I. Introduction

THERE is a significant body of research describing the use of pattern recognition of myoelectric signals to control prosthetic devices [1-7]. A large majority of this work focuses mainly on improving the offline classification accuracy of pre-recorded signals. While these results are all important they fail to address, what may be described as, a semantic gap between research findings and a clinically viable implementation. Recently, renewed international interest towards advancing prosthetics research has pushed the field to provide more clinically relevant outcome measures. Lock *et al.* [8] showed only a very weak correlation between classification accuracy and usability. Hargrove *et al.* [9] found that by including transient contractions in their training data, they could simultaneously improve the results of a virtual clothespin placement task and *decrease* standard classification accuracy. Kuiken *et al.* [10] introduced alternative quantitative usability metrics focused on class selection and motion completion times.

While developing new, more meaningful, outcome measures is an essential part of advancing myoelectric control, it is also informative to examine the source of the disparity between current research and clinical results. One difference relates to the way that myoelectric data are acquired for conventional offline classification. In research, for example, forearm electromyogram (EMG) data are commonly acquired with the subject in a seated position, with their elbow resting on the arm of a chair. This is done because it makes it easier for the subject to perform repeatable contractions across trials, resulting in higher classification accuracies. In a clinical implementation, training data may be collected in the same way but testing usually consists of more task oriented usage scenarios. This requires the user to not only elicit coordinated contractions, but also to elicit those contractions in a wide variety of limb positions. Consider, momentarily, the task of reaching for a glass in a cupboard, filling that glass with water, and then taking a drink. It quickly becomes apparent that the typical prosthetic user requires that the remnant and prosthetic limb operate in a multitude of positions.

Pattern recognition of myoelectric signals, such as that described by Englehart and Hudgins [1], relies on the generation of differentiable and repeatable contractions. Changes in these patterns can erode the performance of the classifier and may result in unusable controllers. Hargrove *et al.* [11] showed that electrode displacement, if unaccounted for during training, could degrade pattern recognition performance. Similarly, changes in the shape and length of muscles caused by limb positioning can result in a form of shift between the signal source and electrode.

In this work, we investigate the effect of changing limb position on classification accuracy.

II. Methodology

A. Experimental Protocol

EMG data corresponding to eight classes of motion were collected from eight healthy normally limbed subjects (7 male, 1 female). All experiments were approved by the

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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~~ dominant forearm (7 right, 1 left), proximal to the elbow, at the position with largest muscle bulk. A reference electrode was placed over the bone of the elbow. Two analog 3-axis accelerometers (Freescale MMA7260QT MEMS) were used in order to record limb position. The first was affixed adjacent to the cuff on the forearm. The second was placed over the biceps brachii, aligned with the forearm accelerometer when the arm was straight and not rotated. Both accelerometers were configured to have a sensitivity of 800mV/g at a range of ±1.5g.

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, all data, including the 6 accelerometer channels (ACCEL), were acquired using a 16 channel 16-bit analog-to-digital converter (USB1616FS from Measurement Computing™) sampling at 1kHz.

Subjects were prompted to elicit contractions corresponding to the following eight classes of motion: wrist flexion/extension, wrist pronation/supination, hand open, power grip, pinch grip, and a no motion/rest class. Each repetition was sustained for 3 seconds and a 3 second rest was given between subsequent repetitions. This was repeated twice in each of the following limb positions:

P1: Arm hanging at side, elbow bent at 90°

P2: Straight arm reaching up (45° from vertical)

P3: Straight arm hanging at side

P4: Straight arm reaching forward (horizontal)

P5: Torso horizontal, straight arm hanging

P6: Humerus hanging at side, elbow fully bent

P7: Humerus reaching forward, elbow bent at 90° (causing forearm to be vertical)

P8: Humerus reaching forward, elbow bent at 90° (humerus rotated inward so forearm is horizontal)

Subjects were encouraged to perform contractions at a repeatable 'medium' force level and given rest periods between trials to minimize fatigue. Some patients noted minor shoulder (deltoid) fatigue. Figure 1 shows ~~examples of~~ the eight ~~the~~ different limb positions used.

B. Data Processing

As this work represented an introductory look at the effect of position on pattern recognition, it was suitable to test the effects using a known control scheme, such as the one described by Englehart and Hudgins [1]. 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.

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 250ms windows, with processing increments of 50ms. TD features were extracted from the EMG data, and the average value of the ACCEL data was calculated for each frame/window. All classifiers were trained using data from the first trial and tested using data from the second trial.

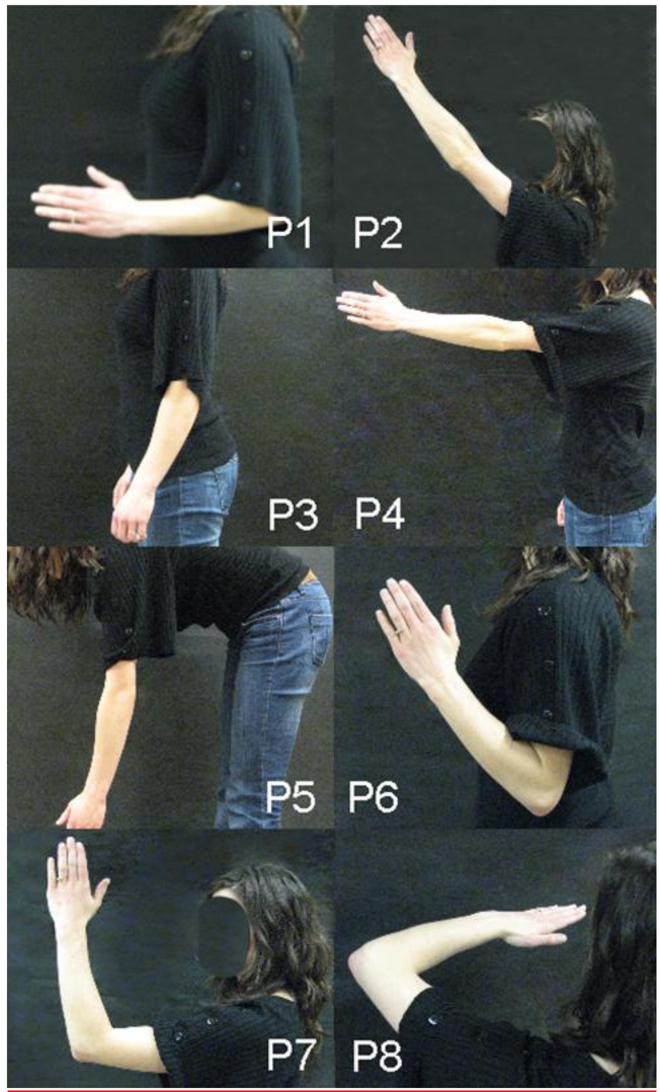

Figure 1: Limb positions collected

III. Results

A. EMG Results

Eight different position-specific classifiers were trained; each one using data from only one of the limb positions, but tested using data from all positions. The resulting matrix of inter-position errors is shown in Table 1. Each entry in the table represents the average error of all motion classes across all subjects. The vertical axis labels denote the training position and the horizontal axis labels denote the testing position. Note that the classification errors shown in the diagonal (which represent the intra-position classification accuracies) are all quite low. Conversely, there is a significant increase in inter-position classification errors, represented by the off-diagonal entries. The mean intra-position classification error was 6.9%, whereas the mean inter-position error was 35.0%.

Table 1: Matrix of inter-position EMG based classification error (%)

	P1	P2	P3	P4	P5	P6	P7	P8
P1	4.7	44.4	28.5	35.6	32.7	35.7	33.6	46.6
P2	35.4	6.7	27.5	23.1	27.5	46.0	34.3	45.2
P3	31.3	33.1	3.3	19.9	13.6	45.6	40.9	46.9
P4	33.3	36.8	17.7	5.1	26.2	44.6	40.0	48.4
P5	27.9	32.7	19.1	18.5	5.7	58.0	35.4	44.5
P6	27.8	47.2	37.0	37.0	44.4	8.9	26.4	41.7
P7	23.2	35.0	34.1	30.2	27.8	30.3	11.3	34.4
P8	37.7	41.2	41.3	41.3	39.2	41.1	32.1	9.4

Table 1 indicates that the variation introduced by changes in limb position is large enough to obscure some of the inter-class differences. As a result, another classifier was trained using data pooled from all positions to determine if the classifier could learn these inter-position differences. Figure 2 shows the resulting classification errors, broken up by test position. The mean error for all classes was 7.4%.

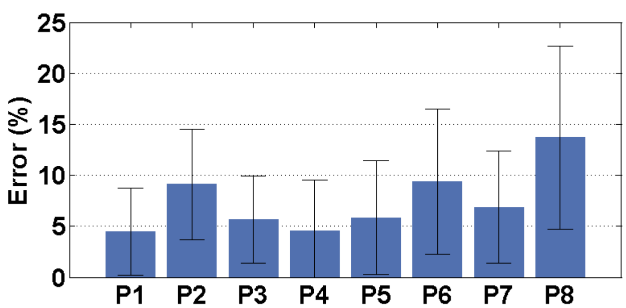

Figure 2: EMG classification error by position when including data from all positions in training

B. Accelerometer Results

In order to take advantage of the lower intra-position errors (shown in green in Table 1), a position specific control scheme would require knowledge of the limb position. In order to test this, three different position classifiers were trained using data from the two accelerometers (ACCEL).

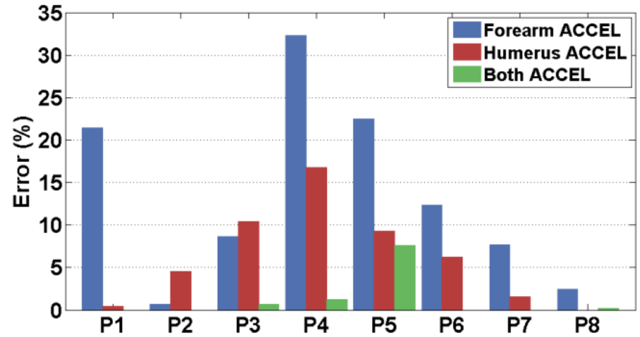

Figure 3: Classification error of limb position when using ACCEL data

The first classifier was trained using data from only the ACCEL on the forearm, the second used only data from the ACCEL on the humerus, and the third was trained using data from both. It should be noted that the forearm ACCEL could more easily be implemented into an existing trans-radial socket design, and should therefore be preferred. Figure 3 shows the position classification errors for all three cases. Figure 4 shows the results of using the position classification outputs to select position-specific classifiers for EMG-based motion classification.

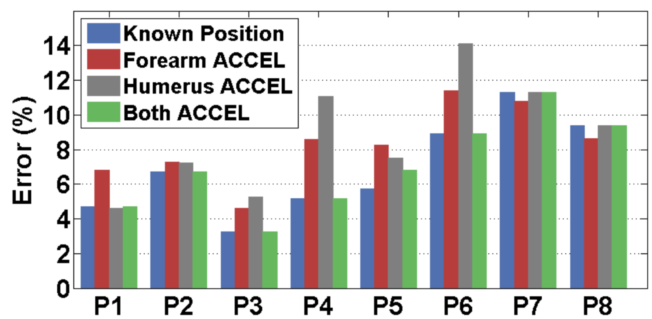

Figure 4: Motion classification error when using a dual-stage approach (classification of position using ACCEL, followed by position-specific EMG classification)

C. Combined EMG and Accelerometer Results

An alternative to the dual-stage approach above (selection of a position specific EMG classifier based on a discrete position classification) is to use the ACCEL data as an additional input to a multi-sensor EMG-ACCEL classifier. In this approach, the ACCEL data was combined with the EMG data, thereby increasing the dimensionality of the LDA space, and removing the need for determination of a discrete position. Figure 5 shows the result of combining one or both ACCEL with the EMG into a single classifier and training using data from all positions. Note that in all positions, the classifiers that included ACCEL data outperformed the EMG only classifier.

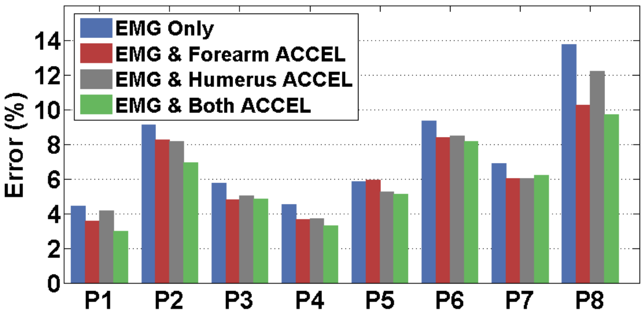

Figure 5: Motion classification error by position when using EMG only and when including ACCEL data

IV. Discussion

These results indicate that EMG classification error is strongly dependent on limb position. This dependence may be attributable to variations in muscle recruitment (for limb stabilization) or muscle geometry (resulting in a form of shift with respect to the electrodes). As a result, ~~I~~it may be insufficient to train a prosthetic control scheme in a single position and expect it to translate well to multi-position use. The degradation shown when changing between positions may contribute to the differences seen between published classification accuracy results and observed clinical performance.

When training in a single position, it was shown that classification rates were much higher within a given position than they were between positions. By using ACCEL data to classify limb position, it was shown that position specific classifiers could be used to reduce the motion classification error substantially. Note that while the overall position error (shown in Figure 3) is higher when using only the forearm ACCEL, the effect on motion classification (shown in Figure 4) is not as significant. A possible explanation for this is that humeral position/orientation (which was often misclassified when using the forearm ACCEL) may have less influence on the EMG than does forearm position/orientation.

While these results show that it is possible to alleviate position effects on EMG based pattern recognition, further analysis is required. The mitigation techniques discussed here~~in~~ all require collection of training data in multiple positions. This may prove to be cumbersome for the end prosthetic user, and therefore, an ideal controller would provide position invariant control after being trained in a single position.

This work represents a pilot study that is part of a larger investigation aimed at improving the clinical robustness of myoelectric control. The results shown here indicate that facilitating position invariant myoelectric control through methods such as feature selection, data projection, multi-sensor systems, or by other means could be an important part of this work.

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