

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

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## Objective

The main objective of this research was to examine the effect of changes in limb position on pattern recognition based myoelectric control and consider strategies to mitigate its effects.

## Background

Pattern recognition based myoelectric control systems perform best under repeatable conditions. As such, the literature often reports classification accuracy of signals recorded from a fixed position. This results in more repeatable patterns and higher accuracies.

Clinical testing, however, focuses more on usability and task oriented problems (such as moving cups/blocks, or lifting objects overhead). These tests invariably force the user to move their limb in various positions, resulting in changes in biomechanics, gravity and socket fit.

The literature has already shown that electrode displacement can degrade pattern recognition performance, therefore it is reasonable to hypothesize that positional changes could have a similar affect.

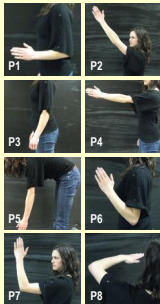
## Experimental Design

8 Subjects  
 • 7 male, 1 female  
 • 7 right, 1 left-dominant

8 classes of motion:  
 • Wrist Flexion/Extension  
 • Wrist Pronation/Supination  
 • Hand Open  
 • Power Grip, Pinch Grip  
 • No Motion

8 channels of EMG  
 • Stainless steel electrodes  
 • LTI differential amplifiers

Two accelerometers (3-axis):  
 1) Over the biceps brachii  
 2) Adjacent to the electrode cuff on the forearm.



The collection of training and test data corresponding to all 8 classes was repeated in each of the 8 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)

## Signal Processing

As this is an introductory study, we chose a commonly reported classification scheme. This control scheme has been used in various research labs investigating the real-time performance of myoelectric control.

EMG data were low pass filtered at 500Hz and notch filtered at 60Hz to remove power line interference.

Time Domain features (mean absolute value, zero-crossings, slope sign changes and "wavelength") were extracted using 250ms windows with 50ms overlap on EMG.

Average values of the accelerometer data were calculated over the same time windows.

Classification was performed using an LDA classifier.

## Results

### Inter-Position

8 different classifiers were trained (each using EMG data from one position only).

Figure 1 shows the results when training in one position and testing in each other position (averaged over all classes).

- Average Intra-position error of 6.9%
- Average Inter-position error of 35.0%
- Average Total Error of 31.4%

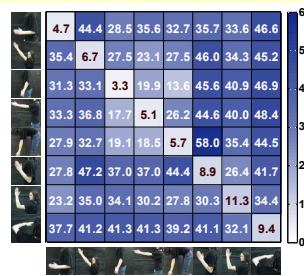


Figure 1: Average Inter-Position Classification Error (%)

### Multi-Position Training

A single classifier was trained using EMG data from all positions. Data from the same classes were pooled irrespective of position.

Figure 2 shows the error (averaged across all users and classes) when testing in the various positions.

- Average error of 7.4%

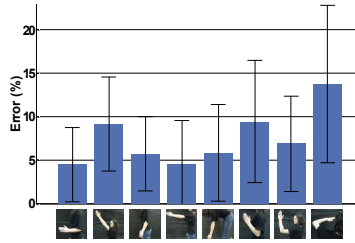


Figure 2: Average Error When Training With All Positions (%)

### Two Tier Classification

A classifier was trained using the accelerometer data, and was used to classify the position of the limb.

Figure 3 shows the position classification results.

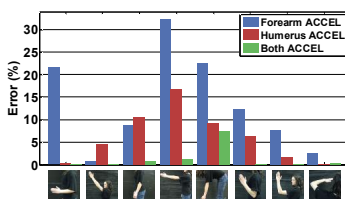


Figure 3: Average Position Classification Error (%)

Data were subsequently classified using position specific EMG classifiers (who's results were shown in Figure 1). Figure 4 shows the final results.

- Average error of 6.9% using known position
- Average error of 7.1% using both accelerometers

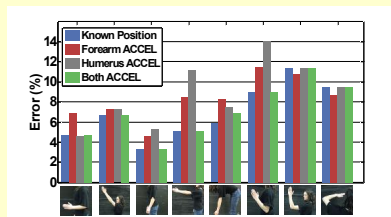


Figure 4: Average Position Specific Classification Error (%)

### Combined Input Classification

A single LDA classifier was trained using both the EMG and accelerometer data. Data from all positions were pooled for each class.

This differs from position specific classification because the accelerometers were used to provide continuous context to the EMG, rather than discrete position.

- Average of 5.9%

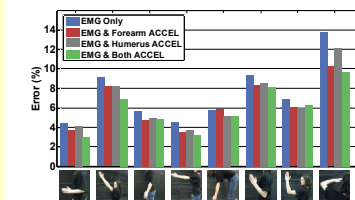


Figure 5: Multi-Input Classification Error (%)

## 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, 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 here, when changing between positions, may contribute to the differences seen between published classification accuracy results and observed clinical performance.

Note that while the overall position error (shown in Figure 3) is higher when using only the forearm accelerometer, 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.

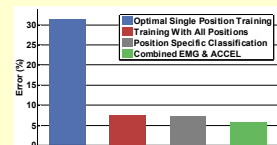


Figure 6: Comparison of Proposed Techniques (%)

## Conclusions

Pattern recognition accuracies were shown to be adversely affected by limb position. Proper training and inclusion of accelerometer data are promising approaches to minimize these effects.

## Ongoing Work

Part of an ongoing study at UNB looking at clinical robustness of pattern recognition-based myoelectric control:

- Effect of position, limb loading, contraction force
- Selective classification for non-ideal conditions

## Acknowledgements



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