Towards better understanding and reducing the effect of limb position on myoelectric upper-limb prostheses

Matthew R. Masters,[1] Ryan J. Smith,[2] Alcimar B. Soares,[3] and Nitish V. Thakor[4]

***Abstract*— Myoelectric control of prosthetic devices tend to rely on classification schemes of extracted features of EMG data. Those features however, may be sensitive to arm position resulting in decreased performance in real-world applications. The effect of varying limb position in a pattern recognition system have been illustrated by documenting the change in classification accuracy as the user achieves particular limb configurations. We continue to investigate this limb position effect by observing its impact on classification accuracy as well as through an analysis of how each extracted feature of the raw EMG varies in each position. Finally, LDA classification schemes are applied both to demonstrate the effect varying limb position has on classification accuracy and to increase classification accuracy without the use of additional hardware or sensors such as accelerometers as has been done in the past. It is shown that high classification accuracy can be achieved by (1) training an LDA classifier with data from many positions, as well as (2) by utilizing an extra position LDA classifier which can weigh the grasp classifiers appropriately. The classification accuracies achieved by these methods approached that of a model relying on a perfect knowledge of arm position.**

I. INTRODUCTION

Although pattern recognition based prostheses have been given significant credit for bringing the user increased degrees of freedom, a significant limitation to pattern recognition prostheses has yet to be overcome. Its accuracy significantly degrades as the user moves from the location in which the system was trained. Many myoelelectric control schemes have been reported as having high classification accuracies [1], [2]. These results however, were achieved in experimental paradigms that largely did not consider the impact of changes in limb position and orientation. These are significant factors as it has been shown that the accuracy of a pattern recognition-based upper-limb myoelectric prostheses is significantly influenced by the position of the limb [3], [4], [5], [6], [7]. It is desirable that the upper-limb prosthetic device maintain its functionality in a wide range of positions so that its usability can be expanded towards a greater number of daily tasks.

The disparity between classification accuracy at the training position and the accuracy of the system when the limb is in a different location has heretofore been referenced as the "limb position effect" [4]. Previously, the effect of varying limb position in pattern recognition systems has been illustrated by documenting the change in classification accuracy as the user achieves a particular limb configuration. The problem has been ameliorated by groups incorporating sensors to discriminate between positions [4], [5], or find features which are not as susceptible to change across limb positions [7]. This paper continues to investigate the limb position effect by observing not only the degradation of classification accuracy, but also, more fundamentally, through analysis of how each extracted feature of the raw EMG varies in each position. Additionally, potential solutions are presented by generating classifiers using Linear Discriminant Analysis (LDA) each having varying degrees of positional awareness. Through a more comprehensive understanding of the issue, one can gain a greater insight into not only why a solution to this issue is necessary but also where the solutions fall short and how future work may advance the field. Finding a solution to the issue is paramount to improve the usability of such a device in day-to-day use.

This material is based upon work supported by the National Science Foundation under Grant No. DGE-1232825 and the National Institute of Health under Grant No. R44NS065495.

[1]M. Masters, [2]R. Smith, and [4]N. Thakor are with the Department of Biomedical Engineering, Johns Hopkins University, Baltimore MD. Corresponding author: `mmaster8 at jhu.edu`

[3]A. Soares is a professor at the Federal University of Uberlandia, Brazil and is a visiting researcher at Johns Hopkins University, Baltimore MD.

II. METHODS

A. Population and Data Acquisition

For this pilot study, EMG data was collected from two able-body patients: Subject 1 - male, age 24, with extensive exposure to pattern-recognition based myoelectric prostheses control; Subject 2 - female, age 25, with no prior exposure to myoelectric control. The first having trained according the model established by [8] in which principles were learned to create "consistent and distinguishable movements through interaction with a visual biofeedback training system" [8].

Eight channels of raw EMG were obtained through differentially amplifying electrode pairs placed approximately equidistant around the circumference of the forearm, approximately three inches distal to the medial epicondyle of the humerus. The electrode pairs were numbered one through eight with the first placed above the extensor carpi ulnaris muscle and the others continuing clockwise around the forearm if viewing a cross section of the forearm looking up the arm. The stainless-steel dome electrodes were inserted into a non-conductive elastic band with options for sizing according to the diameter of the user's forearm. The ground electrode was a Norotrode 20 bipolar Ag/AgCl EMG electrode (Myotronics, Kent, WA) and was placed approximately one inch proximal to the olecranon. The cables connecting the electrodes to the amplifiers and to the data acquisition system were well maintained eliminating extraneous factors and potential artifacts due to pulling forces on the electrodes or rotation of the clips attached to the

978-1-4244-7929-0/14/$26.00 ©2014 IEEE

electrodes. The raw data was amplified after approximately one foot of shielded cable by 13E200 MYOBOCK electrodes (Ottobock, Plymouth, MN) such that saturation did not occur. Following amplification, the signal was sampled using the NI USB-6009 (National Instruments, Austin, TX) at 1000Hz per channel. A subsequent 30-300Hz bandpass and a 60Hz notch filter were applied to the signal as indicated by [8]. Although standard surface EMG signal conditioning usually utilizes a 20-500Hz bandpass filter, the authors decided to narrow that band in order to avoid as much as possible low frequency instabilities due to fast twitching of the stump muscles in a real application (amputees) and noise outside the main band of the power spectrum (below 300Hz). Additionally, the features extracted in this work are not strongly affected by frequencies outside this range.

Each subject performed five unique hand or wrist configurations including rest (R), hand open (O), hand close (C), wrist pronate (P), and wrist supinate (S). These hand and wrist configurations will hereafter be referenced as "grasps." The subjects performed five repetitions of each grasp maintaining the contraction for a duration of four seconds for each repetition. They performed this routine while standing with their arm in seven locations relative to their body, namely: (1) in the neutral (N) position (from anatomical neutral, 90^o elbow flexion and 90^o wrist pronation), (2) in the "upper right" (U-R) location with 135^o shoulder abduction in the sagittal plane, (3) in the "down right" (D-R) location with 45^o shoulder abduction in the sagittal plane, (4) in the "down" (D) location with the shoulder in its anatomical neutral position, (5) in the "down left" (D-L) location with 45^o shoulder flexion and 45^o shoulder adduction, (6) in the "upper left" (U-L) location with 135^o shoulder flexion and 45^o shoulder adduction, and finally (7) in the "upper" (U) location with 135^o shoulder flexion.

B. Data Processing

Time domain (TD) features of the amplified and filtered EMG signals were obtained by imposing a 200ms moving window with 175ms overlap (25ms delay plus processing time). The TD features extracted were mean absolute value (MAV), waveform length (WL), and signal variance (VAR). These features were extracted over others because of prior work suggesting they are sufficient for high classification accuracy in real-time myoelectric control environments [9], [10].

Subsequent LDA classification of the acquired features and the associated grasp was performed. The method in which LDA classification was applied was unique to each of the four scenarios described hereafter. It is shown how the resulting classifiers were utilized in various ways to both demonstrate the effect of varying limb position on classification accuracy and work towards achieving higher classification accuracy. In each case, five fold cross validation was used to estimate classification accuracy. This is performed by using data from four of the five trials of each grasp to train the system and evaluating the resulting classifier on the remaining trial. A classification accuracy percentage is computed for each of the five folds as given by (1).

$$\frac{\text{Number of samples correctly classified}}{\text{Total number of testing samples}} \tag{1}$$

The average of these five individual classification accuracies is reported along with the standard error of the mean.

1) Method 1: Seven unique grasp classifiers are created using the data obtained from each respective location. By applying the classifier corresponding to the current position of the arm, the system has perfect positional awareness and the classifier that was created in the current position of the arm can be applied to incoming data. In so doing, an upper bound for classification accuracy is found given the model parameters (window, extracted features etc.).

2) Method 2: A single grasp classifier was created from training data collected in the neutral position. This classifier is applied to new data obtained in the neutral position as well as to data from the remaining six positions.

3) Method 3: A single grasp classifier was created using training data from all seven locations. In this way, the resulting classifier can be described as an "aggregate" classifier over the seven training locations.

4) Method 4: A position classifier is created whose output weighs each individual grasp classifier accordingly. Thus, if the position classifier is confident that the user's arm is in a particular position, the upper-right position for example, the grasp classifier created from data collected in the upper-right position will have a larger influence on the predicted grasp being performed. In this way, an estimate of arm position influences the degree to which the output of each grasp classifier is considered when making the final estimate of the grasp being performed.

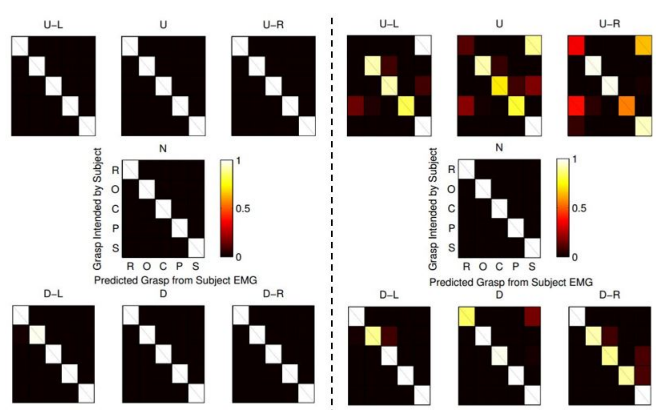

Fig. 1. The seven confusion matrices on each half of the figure represent the seven positions from which training data was obtained from Subject 1. To the left of the dashed line are confusion matrices for the provided cue matching the predicted cue when the classifier is created and applied in the same location. To the right are confusion matrices for the provided cue matching the predicted cue when the classifier is created in the "neutral" position and applied in all locations.

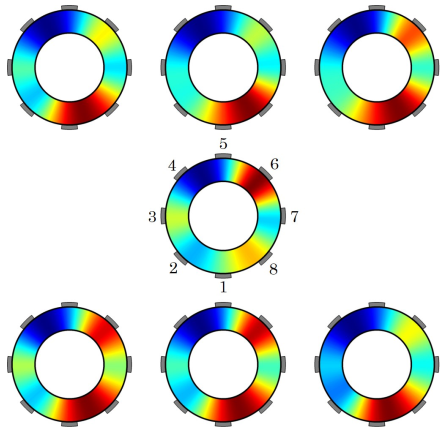

Fig. 2. Periodic cubic spline interpolation of average MAV over the entire grasp period for the "close" grasp in each of the seven locations for Subject 1. The electrode pair numbers are shown around the center ring. Red denotes large MAV values while blue denotes low.

III. RESULTS

A. Illustrations of the Limb Position Effect

The limb position effect is clarified and depicted in this section by providing the results of various analysis methods in the form of (1) confusion matrices, (2) depictions of EMG activity around the circumference of the arm, and (3) through plots of extracted feature behavior during each grasp performed in each position as detected by a single electrode.

Fig. 1 gives a visual representation of the effect limb position variation has on classification accuracy. When the classifier is created and evaluated in the same position, classification accuracy of 98.5±0.2% is achieved. When the classifier is created in the neutral position and evaluated in all positions, classification accuracy decreases to 83.5±0.8%.

The effect of varying limb position in a pattern recognition system have been documented by reporting the change in classification accuracy as the user achieves a particular limb configuration. Although Fig. 1 goes beyond reporting a single value for classification accuracy, it similarly reports classification accuracy as a means for demonstrating the effect. Fig. 2 and Fig. 3 however, shed more light into why classification accuracy degrades as the subject moves from the position in which the classifier was trained.

Fig. 2 shows how MAV recorded by each electrode varies according to arm position while performing the hand-close grasp. Similar results were obtained for the other four grasp types. It can be seen that the MAV values change considerably depending on arm position.

Fig. 3 also shows that extracted feature means vary considerably from position to position. It illustrates that not only MAV means, but the mean of each extracted feature (MAV, WL, and VAR) varies. A one-way ANOVA was used to test this observation that the extracted features differ according to position. With $p<.001$ for each feature and grasp combination, it can be concluded that the features are significantly different across positions. Although the figure only shows the data obtained by one electrode pair, similar results were observed for all electrode pairs. Such a depiction of the limb position effect shows the issue at a more fundamental level.

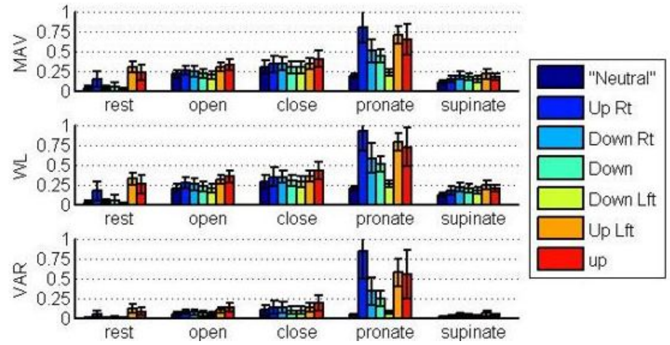

Fig. 3. Normalized mean of the respective feature with error bars representing one standard deviation above and below the mean for each grasp in each position as measured by electrode pair 8 from Subject 1.

TABLE I
RESULTS OF CLASSIFICATION SCHEMES

Method	Classification Accuracy (%)	
	Subject 1	Subject 2
1	98.5±0.2	87.4±1.2
2	83.5±0.8	77.9±0.4
3	96.5±0.3	86.9±0.9
4	96.5±0.7	83.8±1.4

B. LDA Classifiers

1) Method 1: For Subject 1, average classification accuracy when the classifier was created and applied in the same location was 98.5±0.2%. For Subject 2, average classification accuracy in this scenario was 87.4±1.2%.

2) Method 2: For Subject 1, average classification accuracy when the classifier was created in the neutral position and applied in all positions was 83.5±0.8%. For Subject 2, classification accuracy for this scenario was 77.9±0.4%.

3) Method 3: When a single grasp classifier was created using training data from all locations, the classification accuracy for Subject 1 was 96.5±0.3%. Implementing this method for Subject 2 yielded an average classification accuracy of 86.9±0.9%.

4) Method 4: By creating a position classifier whose output applies a weight to the individual grasp classifiers, grasp classification accuracy for Subject 1 was 96.5±0.7% (with position classification accuracy of 43.4±3.3%), while for Subject 2, classification accuracy was 83.8±1.4% (with position classification accuracy of 38.7±2.3%). The result of the position classifier for Subject 2 can be seen in Fig. 4.

The results of the four classification schemes are summarized in Table I.

IV. DISCUSSION

Fig. 1 illustrates that classification accuracy deteriorates when the model receives data from positions different than that where it was trained. In other words, classification

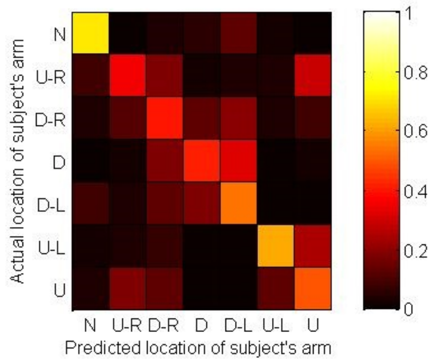

Fig. 4. Confusion matrix of actual position vs predicted position for Subject 2 applied in classification Method 4.

accuracy degrades as the user moves their arm from the location in which the classifier was trained. Thus the claim from previous research is made stronger that the limb position effect is an issue requiring serious attention in order to improve usability to myoelectric pattern-recognition prostheses.

Fig. 2 and Fig. 3 address the issue at a more fundamental level. It is observed that the signals received by each electrode during each grasp type vary significantly across position. Ultimately, it is the changing extracted EMG features that explain the degrading classification accuracy in positions other than where the classifier was trained. Hence, if a classier is trained in the neutral position and is applied to data acquired at different arm positions, one can expect a higher degree of miss-classification.

In an effort to create a more robust system to these variations, four classification methods were explored. The results show that classification accuracy can be increased from the "worst case" scenario (no account for limb position after having created a classifier in one position) without integrating additional sensors such as accelerometers or other inertial measurement units (IMUs). This can be done by either creating an aggregate classifier combining the training data from all locations into one classifier (Method 3), or by incorporating some information about arm position to weigh the individual grasp classifiers appropriately (Method 4). It is worth mentioning that the classification accuracy achieved by these aforementioned methods approached that of the best case scenario given the model parameters in which a perfect knowledge of position was utilized.

Although methods 3 and 4 provided satisfactory improvements in accuracy, the authors argue that Method 4 has a greater potential for further improvement, as it can benefit from real world position information provided by kinematic sensors. The authors have begun work towards this aim which will be the focus of future publication.

V. CONCLUSIONS

The results of this pilot study clearly illustrate the variation in extracted EMG features across limb position and the effect these changes have on classification accuracy. Classification methods 3 and 4 serve to create a more robust myoelectric control scheme of an upper limb prostheses allowing for greater utility of the device.

Having a perfect knowledge of position, classification accuracy of 98.5% and 87.4% is achieved by subjects 1 and 2 respectively. By creating an aggregate classifier created over all space, classification accuracy is 96.5% and 86.9% for each subject respectively. Finally, by weighing each grasp classifier by an estimate of position, accuracies of 96.5% and 83.8% are achieved.

ACKNOWLEDGMENT

The authors would like to thank M.A. Powell for his development of the EMG data acquisition system as well as his guidance and comments regarding our work with myoelectric prostheses control. We would also like to thank the Coordination for the Improvement of Personnel in Higher Education (CAPES-Brazil) and the National Council for Scientific and Technological Development (CNPq-Brazil) for funding.

REFERENCES

[1] A. Simon, L. Hargrove, B. Lock, and T. Kuiken, "A strategy for minimizing the effect of misclassifications during real time pattern recognition myoelectric control," *IEEE Engineering in medicine and biology society conference proceedings*, pp. 1327–1330, 2009.

[2] ——, "Target achievement control test: Evaluating real-time myoelectric pattern-recognition control of multifunctional upper-limb prostheses," *Journal of Rehabilitation Research and Development*, vol. 48, no. 6, pp. 619–628, 2011.

[3] E. Scheme and K. Engelart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use," *Journal of Rehabilitation Research Development*, vol. 48, no. 6, 2011.

[4] A. Fougner, E. Scheme, A. Chan, K. Englehart, and O. Stavdahl, "Resolving the limb position effect in myoelectric pattern recognition," *Neural Systems and Rehabilitation Engineering*, vol. 19, no. 6, pp. 644–651, 2011.

[5] Y. Geng, P. Zhau, and G. Li, "Toward attenuating the impact of arm positions on electromyography pattern-recognition based motion classification in transradial amputees," *Journal of NeuroEngineering and Rehabilitation*, vol. 9, no. 74, 2012.

[6] A. Boschmann and M. Platzner, "Reducing the limb position effect in pattern recognition based myoelectric control using a high density electrode array," *Biosignals and Biorobotics Conference*, pp. 1–5, 2013.

[7] R. N. Khushaba, M. Takruri, J. V. Miro, and S. Kodagoda, "Towards limb position invariant myoelectric pattern recognition using time-dependent spectral features," *Neural Networks*, vol. 55, no. 0, pp. 42 – 58, 2014.

[8] M. Powell and N. V. Thakor, "A training strategy for learning pattern recognition control for myoelectric prostheses," *American Academy of Orthotists and Prosthetists*, vol. 25, no. 1, 2013.

[9] A. Radmand, E. Scheme, P. Kyberd, and K. Englehart, "Investigation of optimum pattern recognition methods for robust myoelectric control during dynamic limb movement," *36th Canadian Medical and Biological Engineering Conference*, 2013.

[10] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 7, pp. 848–54, 2003.