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# A Control System for a Powered Prosthesis Using Positional and Myoelectric Inputs from the Shoulder Complex

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*Abstract*—**The integration of multiple input sources within a control strategy for powered upper limb prostheses could provide smoother, more intuitive multi-joint reaching movements based on the user's intended motion. The work presented in this paper presents the results of using myoelectric signals (MES) of the shoulder area in combination with the position of the shoulder as input sources to multiple linear discriminant analysis classifiers. Such an approach may provide users with control signals capable of controlling three degrees of freedom (DOF). This work is another important step in the development of hybrid systems that will enable simultaneous control of multiple degrees of freedom used for reaching tasks in a prosthetic limb.**

## I. Introduction

The use of shoulder movement as a control source has been well documented for the past several decades. Several studies have evaluated its ability to provide reliable command inputs to functional neuromuscular stimulation (FNS) systems [1,2]. The use of shoulder EMG has also been used in various FNS studies [3,4,5] as well as prosthetic applications [6]. Fewer studies, however, have focused on the possible use of shoulder movement and EMG as combined input sources for the control of prosthetic limbs.

The conventional approach to controlling a prosthetic limb using myoelectric signals may be termed *direct control*. This approach uses the amplitude from MES control sites on the agonist and antagonist muscles to actuate the prosthetic device [7,8]. It provides a proportional means of controlling the desired velocity for a given DOF. Clinically implemented control systems are typically a variation of this control scheme while more advanced strategies are only recently being evaluated within a clinical setting [9]. Such sophisticated strategies often consist of classifiers that recognize the contraction patterns within the MES [10]. These classifiers are trained using feature sets extracted from a user's MES thus allowing the system to be adapted specifically to the user. Various characteristics of this control scheme, including a variety of feature sets and classifiers, have been investigated [10]. Previous work has demonstrated that high classification accuracy can be achieved by using time-domain (TD) features sets as inputs to linear discriminant analysis (LDA) classifiers [11].

Previous work [12] seems to indicate that it may be possible to reliably acquire input sources, to control a prosthetic limb, from the MES resulting from shoulder movements. This work illustrates how synergistic muscle contractions and residual movement from the shoulder complex combined with a classification scheme can be exploited and used to develop several useful classifiers for the control of prosthetic limbs.

## II. Methodology

Two separate experiments were performed to investigate the use of linear discriminant analysis classifiers for both shoulder motion and humeral rotation classification. The experimental protocol and data processing for both experiments are first described prior to presenting the results.

The Research Ethics Board of the University of New Brunswick approved the experimental procedure used for this research and each subject provided informed consent prior to participating in the experiment.

### *A. Shoulder Motion Experiment Protocol*

Data corresponding to nine classes of shoulder motion were collected from six healthy subjects. Scapular movement was recorded using a two-degree-of-freedom joystick mounted to an experimental apparatus setup and attached to a reference electrode located on the acromium bone landmark of the shoulder (Figure 1).

Subjects were instructed to complete the following nine shoulder motion combinations: elevation, elevation/protraction, protraction, depression/protraction, depression, depression/retraction, retraction, elevation/retraction and a no movement/rest class. Each motion was started from the rest position and lasted four seconds. The entire set was repeated eight times. The first four repetitions were used as training data while the remaining data were used for testing.

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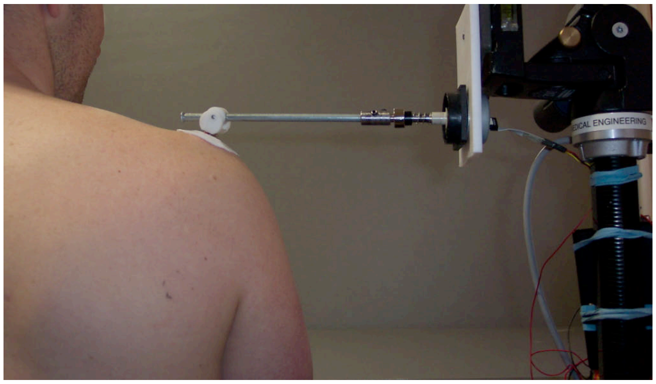

**Figure 1: Experimental Apparatus used for Shoulder Motion Data Collection**

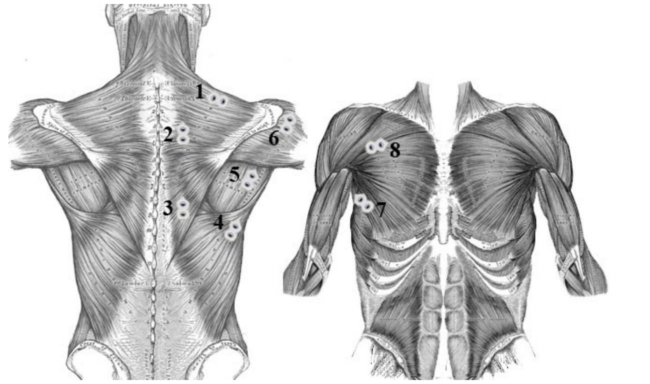


**Figure 2: The electrode placement locations used during the humeral rotation experiment:**

1. **Upper trapezius/Supraspinatus area**
2. **Middle trapezius/Rhomboid area**
3. **Lower trapezius**
4. **Latissimus dorsi**
5. **Infraspinatus/Teres area**
6. **Medial deltoid area**
7. **Serratus anterior**
8. **Pectoralis major area**

### *B. Humeral Rotation Experiment Protocol*

MES data corresponding to nine classes of shoulder motion were also collected from six healthy subjects. Eight Ag-AgCl Duotrode electrodes (Myotronics, 6140) were placed at physiologically relevant locations for shoulder girdle motions and humeral rotation (Figure 2).

Subjects were instructed to complete the same shoulder motion combinations as in the shoulder motion experiment protocol. In addition, subjects were asked to perform two isometric contractions: medial and lateral rotation of the humerus. Each motion or contraction was held at a constant position for four seconds and the entire set was repeated six times.

Additional data sets were collected where subjects were asked to perform one of the two isometric contractions while holding the constant position for one of the nine shoulder movements. Again, each motion/contraction was held for four seconds and the entire set was repeated six times.

The first three repetitions were used as training data, and the remaining data were used for testing. The data were amplified using a gain of 20, high pass filtered at 5 Hz, low pass filtered at 500 Hz, and acquired at 1 kHz using a 16-bit analog-to-digital converter.

### *C. Shoulder Motion Experiment Data Processing*

The data obtained from the joystick apparatus were not altered prior to being used as classifier inputs. The classifier consisted of all nine shoulder motion classes.

### *D. Humeral Rotation Experiment Data Processing*

A feature set consisting of time domain (TD) statistics, used previously in real time MES control schemes [10,13,14] was used to process the EMG data. Other feature sets based on autoregressive coefficients [15] or time-frequency information [16] were not investigated since previous research revealed that there were no significant improvements in performance when using other feature sets in the given setting. The humeral rotation classifier included the two humeral rotation and no movement/rest classes. The optimal number of channels used to extract the features, train and test the classifier was also investigated. Classifiers based on all possible channel combinations were trained and evaluated.

## III. Results

The prediction plot, shown in Figure 3, presents the classification performance of a representative subject for the shoulder motion classifier. Presenting the results in this format illustrates the classifier's ability to accurately identify each of the desired motions based on the joystick inputs. The classifier's overall accuracy across all subjects was found to be 83.28%. Considerable misclassifications to the rest state can be observed. These errors can directly be attributed to the transient portions of the data collected during the experiment. Since subjects were asked to start any movement from the rest state, a fraction of the data will be misclassified before the subject had time to move and reach a steady state position for the requested class. Removing these misclassifications from the test data set provides a more suitable means of evaluating the classifier performance. The classifier's overall accuracy across all subjects was found to be 91.19% when removing the mislabeled data points from the test data set.

The decision boundaries of the joystick input space is shown in Figure 4. This plot demonstrates how the LDA classifier adapted to the representative's range of motion based on the training data set.

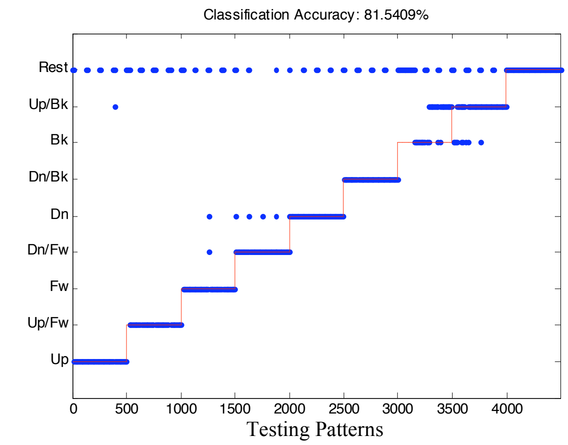


**Figure 3: Prediction plot of a representative subject showing the class decisions for the test data set.**

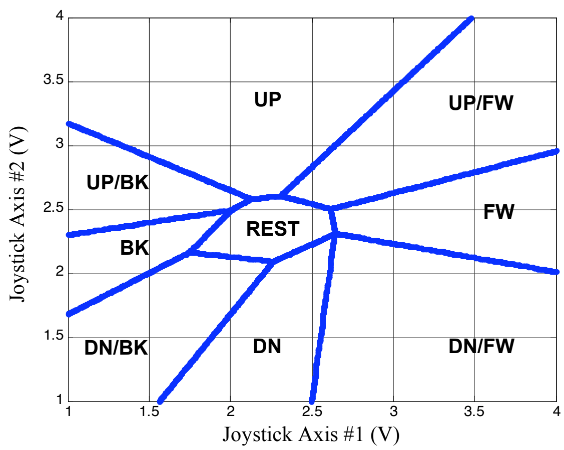


**Figure 4: Decision boundaries of a representative subject showing the class decisions for the joystick input ranges.**

Figure 5 shows the multi-channel classification performance, averaged across all subjects, using the TD feature set for the humeral rotation classifier. The maximum classification accuracy was found to be 96.32% and occurred when using six MES channels. Minimal classification performance variance can be seen when using a different number of MES channels.

## IV. Discussion

The performance results of the shoulder motion classifier seem to indicate that it is possible to accurately classify different shoulder movements. Misclassifications were often present in the depression and retraction movement combinations (i.e. bk and dn) that may be explained by the subject's limited range of motion in those areas.

The use of shoulder position based LDA classifiers also seem to provide benefits that are often not associated with typical shoulder movement control schemes. The classifier will adjust the decision boundaries of the system based on the user's range of motion. The LDA can also provide some level of flexibility in terms of misalignment of the shoulder measuring device as the classification algorithm will adapt to any input variations during the initial training stage.

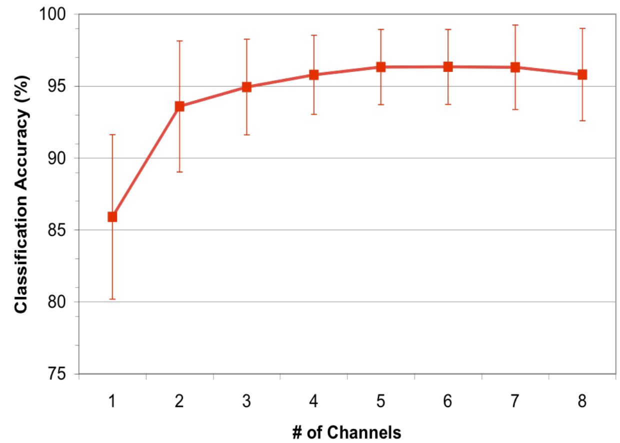


**Figure 5: Classification accuracy of the humeral rotation test data set. The results are averaged across all subjects (n = 6). Error bars are shown at plus/minus one standard deviation.**

The performance of the humeral rotation classifier shows its ability to separate the EMG elicited during normal shoulder and humeral rotation movements. Decreasing the number of channels produced only minor degradations to the classifier performance. Minimizing the required number of electrodes needed for accurate classification is an attractive benefit of using such a system.

Based on these classification results, it is conceivable that implementing both classifiers could result in a system that is capable of controlling three DOF. Further investigation is ongoing to evaluate the prosthetic usability when combined with various control strategies (e.g. endpoint, joint position/velocity, torque-based control schemes). Previous research has shown that usability may vary significantly when compared to classifier performance [17]. The development and implementation of appropriate qualitative and quantitative clinical tests are being investigated to further evaluate the efficacy of these control schemes.

## V. Conclusion

Pattern recognition classifiers were implemented using both the positional data from residual shoulder movements and the resulting MES generated during humeral rotation. The classification accuracy was found to be 91.19% and 96.32%, respectively. The effects of channel reduction were also investigated for the humeral rotation classifier. As few as two EMG channels could be used without significantly compromising classification accuracy.

Current research is addressing the usability of these classifiers in controlling multiple DOF of a prosthetic limb. The implementation of these systems must be assessed regarding its ability to enhance the prosthetic user's ability to perform tasks of active daily living.

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