RESIDUAL SHOULDER MOTION MES CLASSIFIER

Yves Losier, Kevin Englehart and Bernie Hudgins
Institute of Biomedical Engineering, University of New Brunswick, Fredericton, Canada.

ABSTRACT

The integration of multiple control strategies into a hybrid system could allow a prosthesis user to perform smoother, multi-joint reaching movements while reducing the necessary mental effort. This work illustrates the usefulness of the shoulder myoelectric signal as an input source to a control strategy by extracting time domain features from these signals and using a linear discriminant analysis classifier to recognize the user's intended motion. This work is an important first step for future development of hybrid systems that will enable simultaneous control of multiple degrees of freedom used for reaching tasks in a prosthetic limb.

INTRODUCTION

The development of control systems for prosthetic devices has often relied on the use of residual limb motion to allow the user to control several degrees of freedom (DOF). The most common approach is the use of cables, which has been in use for several decades. Externally powered systems also exist where sensors such as force-sensitive resistors and rocker switches are used as primary or additional inputs. This approach is by no means ideal as it may often require considerable training in order to achieve an acceptable level of control of the required DOF. Amputees often still favor the cable-operated system since it offers simpler operation of the prosthetic devices, and also provides some level of proprioceptive feedback to the operator. Other approaches, particularly myoelectric signal (MES) based controllers, have not yet offered a viable and effective alternative.

The conventional approach to myoelectric control (also termed "direct control") uses amplitude coding of the MES from either one or two control sites to actuate the prosthetic device [1,2]. Such a strategy provides a means of controlling the desired DOF in a manner proportional to the desired velocity. Traditional and commercially available control systems are typically a variation of this control scheme while more advanced strategies have yet to be fully implemented in a clinical setting.

Currently, it is nearly impossible to reliably control a large number of DOF simultaneously in an intuitive manner using an amplitude based control system. For high-level amputees, the required number of control inputs far exceeds the number of available voluntarily controlled MES sites. As a result, attempts to directly control multiple DOF simultaneously increases the mental burden placed on the user. Moreover, complex synergistic muscle groups actuate some DOF in an manner that does not allow effective one-to-one mapping. The shoulder joint is a prime example of such a situation, which provides further motivation for the use of residual limb motion as a control source for prosthetic control systems.

Other sophisticated myoelectric control schemes consist of pattern classifiers to recognize the contraction patterns within the MES [3]. To accomplish this, MES patterns are acquired from a user, features are extracted, and used to train a classifier. Many variations of this control scheme, including a variety of feature sets and classifiers, have been investigated [3].

The MES originating from the shoulder complex has so far been a less effective primary input source for prosthetic control. This work demonstrates how synergistic muscle contractions from the shoulder complex, in combination with advanced myoelectric control schemes, can be exploited and used to develop a pattern recognition based myoelectric controller.

METHODOLOGY

<u>Experimental Protocol</u>
MES data corresponding to eleven classes of motion were collected from five healthy subjects. Eight Ag-AgCl Duotrode electrodes (Myotronics, 6140) were placed at physiologically relevant locations for shoulder girdle motions (Figure 1).

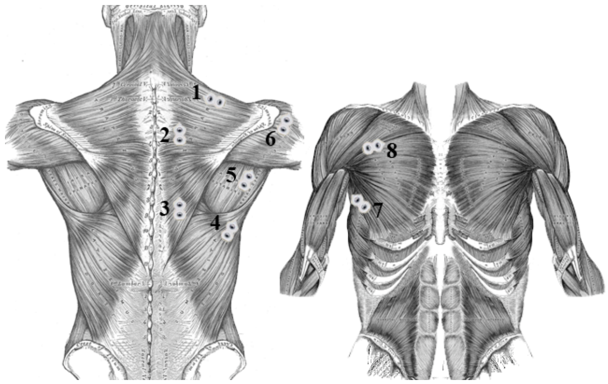

Figure 1: The electrode placement locations used during the experiment:

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**

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

Subjects were instructed to complete nine combinations of shoulder girdle motions: elevation, elevation/protraction, protraction, depression/ protraction, depression, depression/retraction, retraction, elevation/retraction and a no movement/rest class. In addition, subjects were asked to perform two isometric contractions: medial and lateral rotation of the humerus. Each motion or 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, low pass filtered at 500 Hz, and acquired at 1 kHz using a 16-bit analog-to-digital converter.

Data Processing

A feature set consisting of time domain (TD) statistics, used previously in real time MES control schemes [3,4,5] was used to process the data. Included in the TD set are: the number of zero crossings, the waveform length, the number of slope sign changes and the mean absolute value for a given data window. The data from each channel was segmented into window frames of 250ms from which these features were computed. The features from each channel were then concatenated into an aggregate feature vector and used as inputs to a linear discriminant analysis classifier. Other feature sets were investigated, but these were shown not to provide any significant improvement in performance.

Two separate classifiers were created using the feature sets. The first consisted of only seven motion classes: elevation, depression, protraction, retraction, medial and lateral humeral rotation, and no movement. The second classifier included the additional four motion classes that were considered to be combinations of the elevation/depression and protraction/retraction motion classes. The seven-motion class problem incorporates movements used during shoulder displacement, which elicit the muscle synergies in a more fundamental manner as compared to the eleven-motion class problem. Additionally, using a seven-motion classifier would only allow movements to be executed using sequential activation of the DOF in question while the eleven-motion classifier would enable simultaneous multi-DOF control due to the combined nature of the four additional classes.

The optimal number of channels used to extract the features, train and test the classifiers was also investigated. Classifiers based on all possible channel combinations were trained and evaluated. The classifiers were then ranked, on a subject-by-subject basis in terms of their classification accuracy. The process was repeated for i channel data sets (where i=1:8). The classification accuracy of the optimal channel combination for each i channel data sets was recorded on a subject-wise basis. The optimal group-wise results were also calculated using a cost metric based on the ranking of the channel combinations for each subject.

RESULTS

The confusion matrix, shown in Figure 2, presents the eight-channel classification performance, averaged across all subjects, using the TD feature set for the seven motions case. Presenting the results in this format illustrates the classifier's ability to accurately identify each of the desired motions. The classifier's overall accuracy was found to be 93.6%. Figure 3 shows the eight-channel classification performance, averaged across all subjects, using the TD feature set for the eleven motions case. A drop in classification accuracy was observed for all corresponding classes when compared to the seven motions case. The overall classification accuracy was found to be 88.5%. Another classification measure, termed *adjacent classification*, was also used to underscore the misclassifications, which were one of the discrete motions used in the combined motion classes. Its value was found to be 3.6% thus labeling 7.9% of the classifications as incorrect.

Figures 4 and 5 display the overall classification accuracy (averaged across all subjects) for both the optimal subject-wise and group-wise channel combinations for the seven and eleven class cases, respectively. In both cases, the highest accuracy achieved, using the group wise channel combinations, occurred when all eight MES channels were included.

DISCUSSION

The performance results of the classifiers seem to indicate that the protraction and depression motions as well as the retraction and elevation motions pair are major contributors to classification error. This may be explained by the highly correlated actuation of synergistic shoulder muscles used for these movements. Re-assessing the optimal electrode placement may alleviate this problem by attempting to find highly uncorrelated MES locations, which would increase the separability of the classes in question.

An attempt to reduce the number of channels resulted in a decrease in classification accuracy. It should be mentioned however, that increasing the number of channels beyond five produced only minor improvements to the classifier performance. Additionally, the differences shown on both plots between the group-wise and subject-wise results

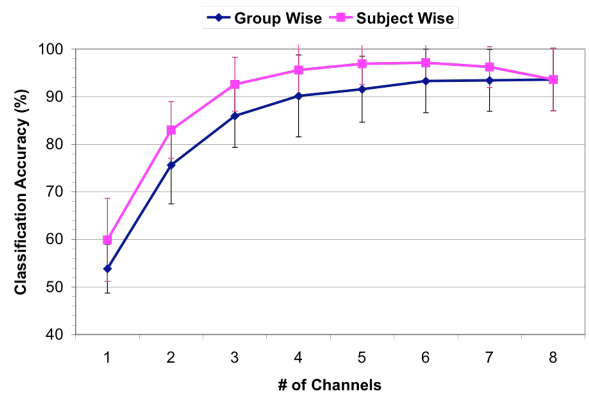

Figure 4: Classification performance for seven-class case.

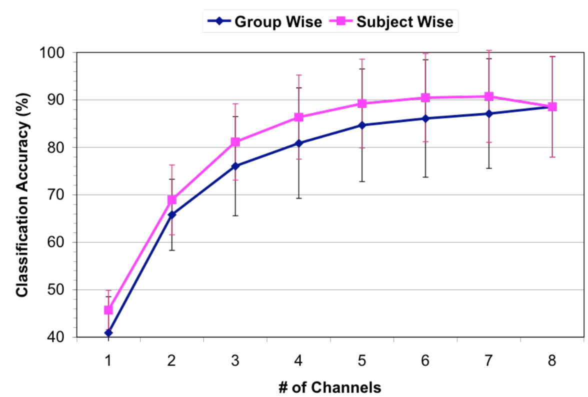

Figure 5: Classification performance for eleven-class case.

	Elevation	Protraction	Depression	Retraction	Medial Rotation	Lateral Rotation	Rest
Elevation	100.00	0.00	0.00	2.66	0.00	0.00	0.00
Protraction	0.00	79.62	12.07	0.11	0.00	0.00	0.43
Depression	0.00	19.78	87.17	0.00	0.00	0.00	0.00
Retraction	0.00	0.00	0.00	96.74	0.00	0.00	0.00
Medial Rotation	0.00	0.00	0.00	0.00	100.00	7.61	0.00
Lateral Rotation	0.00	0.00	0.00	0.00	0.00	92.39	0.00
Rest	0.00	0.60	0.76	0.49	0.00	0.00	99.57

Figure 2: A classification confusion matrix, averaged across all subjects, for seven discrete motions using the TD feature set. The shaded areas represent accurate motion classification while the remainder of the respective column represents incorrect classification for the given motion.

	Elevation	Elevation/ Protraction	Protraction	Depression/ Protraction	Depression	Depression/ Retraction	Retraction	Elevation/ Retraction	Medial Rotation	Lateral Rotation	Rest
Elevation	91.36	2.23	0.00	0.00	0.00	0.16	0.98	8.97	0.00	0.00	0.00
Elevation/Protraction	7.83	83.86	2.88	0.00	0.00	0.00	0.00	0.00	1.36	0.00	0.00
Protraction	0.00	3.64	68.42	10.38	2.01	1.74	0.11	0.98	0.00	0.00	1.20
Depression/Protraction	0.00	0.00	14.67	78.64	7.61	0.00	0.00	0.00	0.00	0.00	0.00
Depression	0.00	0.05	13.26	10.98	89.95	1.03	0.00	0.00	0.00	0.00	0.00
Depression/Retraction	0.43	0.00	0.00	0.00	0.00	95.11	2.77	0.00	0.00	0.00	0.00
Retraction	0.00	0.00	0.00	0.00	0.00	1.79	88.15	0.00	0.00	0.00	0.00
Elevation/Retraction	0.38	0.00	0.00	0.00	0.00	0.00	7.93	89.84	0.00	0.00	0.00
Medial Rotation	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	98.42	8.75	0.00
Lateral Rotation	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.00	91.25	0.00
Rest	0.00	10.22	0.76	0.00	0.43	0.16	0.05	0.00	0.22	0.00	98.80

Figure 3: A classification confusion matrix for eleven motions using the TD feature set, averaged across all subjects. The dark shaded areas represent accurate motion classification while the results found within the lightly shaded areas represent adjacent misclassification during combined motion performance. The remainder of the respective column represents incorrect classification for the given motion.

indicate that the ideal channel subset varied between subjects.

These classification results, although promising, are not indicative of actual 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 [6]. The development of appropriate qualitative and quantitative clinical tests is required to further investigate the efficacy of these control schemes.

CONCLUSION

A pattern classification scheme was implemented using the MES generated during residual shoulder girdle movements. The effects of various features sets as well as reduced channel combination subsets were also investigated. Minimal classification performance variance was observed when using different feature sets. The accuracy was found to be 93.6% and 88.5% when classifying seven and eleven classes, respectively. Reducing the number of channels used to extract the features decreased the classifiers' performance, although five appropriately chosen channels provided near-optimal performance.

Further research is required to evaluate the usability of these MES based classifiers in controlling multiple DOF of a prosthetic limb. Ultimately, the usefulness of these schemes must be assessed on its ability to intuitively and reliably enhance the prosthetic user's ability to perform tasks of active daily living. Work is currently ongoing to develop functional tests to achieve those goals.

ACKNOWLEDGEMENTS

This work was supported by NSERC Discovery Grants 171368-03 and 217354-01, the Research Assistantship Initiative (RAI) of the New Brunswick Innovation Foundation (NBIF), and the Atlantic Innovation Fund (AIF).

REFERENCES

[1] D. S. Dorcas, and R. N. Scott, "A three-state myoelectric control," *Med. Biol. Eng.*, vol. 4, pp. 367-372, 1966.

[2] D. A. Childress, "A myoelectric three state controller using rate sensitivity," *in Proc. 8th ICMBE*, Chicago, IL, pp. S4-S576, 1969.

[3] K. Englehart, and B. Hudgins, "A robust, real time control scheme for multifunction myoelectric control," *IEEE Trans. on Biomedical Engineering*, vol. 50, no. 7, pp. 848-854, July 2003.

[4] B. Hudgins, P. A. Parker and R. N. Scott, "A new strategy for multifunction myoelectric control," *IEEE Trans. on Biomedical Engineering*, vol. BME-40, pp. 82-94, 1993.

[5] Y. Huang, K. Englehart, B. Hudgins, and A. D. C. Chang, "A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses," *IEEE Trans. on Biomedical Engineering*, vol. 52, no. 11, pp. 1801-1811, November 2005.

[6] B. Lock, K. Englehart, and B. Hudgins, "Design and interactive assessment of continuous multifunction myoelectric control systems," *Proceedings of the Myoelectric Controls Symposium '05*, Fredericton, Canada, August 2005