From "MEC 11 Raising the Standard," Proceedings of the 2011 MyoElectric Controls/Powered Prosthetics Symposium Fredericton, New Brunswick, Canada: August 14-19, 2011. Copyright University of New Brunswick.

RESOLVING THE LIMB POSITION EFFECT

Anders Fougner[1], Erik Scheme[2], Adrian D. C. Chan[3], Kevin Englehart[2], and Øyvind Stavdahl[1]

[1]*Department of Engineering Cybernetics, Norwegian University of Science and Technology, Trondheim, Norway*
[2]*Institute of Biomedical Engineering, University of New Brunswick, Fredericton NB, Canada*
[3]*Department of Systems & Computer Engineering, Carleton University, Ottawa ON, Canada*

INTRODUCTION

Electromyography (EMG) has been used as a control input for powered upper limb prostheses for decades. Alternative biosensors, like myokinemetric sensors [1],[2], mechanomyographic sensors [3] and accelerometers [4] have been used for upper limb pattern recognition in more general terms but have not produced accuracies acceptable for prosthetic use.

The desire to use a larger number of myoelectrode sites to facilitate control of multiple degrees of freedom has been counteracted by the added complexity, cost, space, and weight associated with additional sites. Thus, commercial upper limb prostheses today usually have only two electrode sites, while researchers continue to experiment with multiple sites [5]. An alternative to the uni-modal EMG approach for increasing the degrees of freedom is a multi-modal approach. Instead of adding additional EMG channels, it is possible to combine EMG and other sensor modalities (e.g., force sensors [6] or accelerometers [7]) in order to improve pattern recognition performance. Other examples of multi-modal solutions exist [8], [9].

In our previous work [10] it was shown that variations in limb position associated with normal use can have a substantial impact on the robustness of myoelectric pattern recognition. We proposed to solve this problem, hereafter referred to as the *limb position effect,* by training the classifier in multiple positions and by measuring the limb position with accelerometers. Applying these methods to data from normally limbed subjects, the classification errors were reduced substantially.

In the present study, we have examined the generalizability of the training set as a function of the number of training positions in the set. This makes it possible to define a minimum training procedure, in order to reduce the training time for the end user.

Finally, we have investigated accelerometers as a supplementary modality for EMG. Accelerometers are relatively cheap, small, robust to noise and easy to integrate in a prosthetic socket. This work examines the efficacy of accelerometers in comparison to adding expensive and space-consuming electrode sites.

METHODS

All experiments were approved by the University of New Brunswick’s Research Ethics Board.

A. Population and Data Acquisition

EMG data corresponding to eight classes of motion were collected from 17 healthy normally limbed subjects (10 male, 7 female) within the age range 18 to 34 years.

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 (EL12 by Liberating Technologies, Inc.). The cuff was placed around the dominant forearm (13 right, 4 left), proximal to the elbow, at the position with largest muscle bulk. A reference electrode (RedDot by 3M) was placed over the back of the hand. Two analog 3-axis accelerometers (Freescale MMA7260QT MEMS) were used to estimate limb position. The first accelerometer was affixed adjacent to the cuff on the forearm, over the brachioradialis muscle. The second was placed over the biceps brachii, aligned with the forearm accelerometer when the subject was reaching forward (see position P2 in Fig. 1). Both accelerometers were configured to have a sensitivity of 800 mV/g at a range of ±1.5 g, where g represents acceleration due to gravity.

The eight channels of EMG were differentially amplified using remote AC electrode-amplifiers (BE328 by Liberating Technologies, Inc.), and low pass filtered at 500Hz with a 5th order Butterworth filter. Finally, the six accelerometer channels and eight EMG channels were acquired using a 16-bit analog-to-digital converter (USB1616FS by Measurement Computing) sampling at 1 kHz.

Subjects were prompted to elicit contractions corresponding to the eight classes of motion shown in Table 1**Error! Reference source not found.**. Performance was evaluated using all eight classes, as well as a reduced set of five classes. This five class system only included classes C3, C4, C5, C6, and C8, which are representative of contemporary powered prostheses. The five class system is referred to as the *contemporary* system and the eight class system as the *advanced* system.

Table 1: Motion classes

C1.	**Wrist flexion**	**C5.**	**Open hand**
C2.	**Wrist extension**	**C6.**	**Power grip**
C3.	**Pronation**	**C7.**	**Pinch grip**
C4.	**Supination**	**C8.**	**Hand at rest**

Each contraction was sustained for three seconds and a three second rest was given between subsequent contractions. Ten trials were recorded in each of the following limb positions (P1–P5; as illustrated in Fig. 1), resulting in a total data set of [n subjects × 10 trials × 5 positions × 8 classes × 3 seconds], where n is explained in Section C.

Fig. 1: Limb positions.

Subjects were instructed to perform contractions at a moderate and repeatable force level and given rest periods between trials to avoid fatigue. The average duration of the experiment (with 50 trials lasting 48 seconds each) was approximately 80 minutes per subject. Some patients noted minor shoulder (deltoid) fatigue.

B. Data processing

As this work represents an introductory examination of multi-modal pattern recognition, it was appropriate to test the effects using a known control scheme. Englehart and Hudgins [11] showed that simple time-domain (TD) feature extraction combined with a linear discriminant analysis (LDA) classifier can 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 and was therefore adopted in the present study. EMG data were digitally notch filtered at 60 Hz using a 3rd order Butterworth filter in order to attenuate any power line interference. Data were segmented for feature extraction using 250 ms windows, with processing increments of 50 ms. The TD features (mean absolute value, zero crossings, number of turns and waveform length) were extracted from the EMG data. Please refer to [11] for details of the feature extraction and the classification.

For each processing window, the average value of the accelerometer data was calculated. Where applicable, this feature (hereafter called ACCEL) was input to the LDA classifier separately or as an extension of the original feature set.

C. Data exclusion

Some of the subjects were not able to perform consistently throughout the data set. Similar phenomena occur in real-life situations where some individuals have great difficulty producing distinct EMG signals [12]. To ensure consistent data, subjects whose intra-position classification error exceeded 10% (five of the 17 subjects) were excluded from the study. This does not detract from the focus of this work; to ascertain the effects of position on performance. It simply eliminates possible confounding factors that may have been present with those subjects that did not perform well.

In two of the remaining 12 subjects, hardware problems caused erroneous accelerometer readings. Thus, 10 subjects were used in this study.

D. Classification

The following classifier training schemes were explored:

1) *Training in a single limb position*
TD features recorded from a single limb position were used to train the classifier. The classifiers were trained using data from the first five trials and tested using data from the last five trials.

2) *Training in multiple limb positions*
TD features recorded in multiple limb positions were concatenated and used to train the classifier. The classifiers were trained using a data set of reduced size per position, so that the total training set size was the same as in 1), in order to make the results comparable.

3) *Training with TD and ACCEL features*
TD and ACCEL features recorded in multiple positions were concatenated and used for motion classification. The data set was reduced in the same way as in 2) in order to make the results comparable.

E. "Leave-One-Out" training strategy

In order to investigate the generalizability of the training set as a function of the number of training positions in the set, the following procedure was employed. For each test position, all possible subsets of the remaining positions were applied as a training set.

F. Input selection

A signal feature selection scheme was chosen in order to examine which electrode sites and accelerometer signals would be most useful for the pattern recognition. Starting with just one sensor, the best one was chosen (based on the classification error averaged over all subjects and motion classes). It was then tested in combination with each of the remaining sensors, and the best combination was chosen before adding the next sensor. In this manner the sensors were added to the system one by one.

From "MEC 11 Raising the Standard," Proceedings of the 2011 MyoElectric Controls/Powered Prosthetics Symposium Fredericton, New Brunswick, Canada: August 14-19, 2011. Copyright University of New Brunswick.

RESULTS

A. Training in a single limb position

Five 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 intra-position and inter-position errors are shown in Table 2.

Table 2: Intra- and inter-position classification errors for the advanced system, trained in a single limb position, and averaged across all subjects and classes.

Intra-position classification error	**3.8%**
Inter-position classification error	**21.1%**
Overall classification error	**17.6%**

B. Training in multiple positions

In Fig. 2, we present a comparison of how training in multiple positions affects the classification, for the *advanced* system. We have used the *Leave-One-Out* strategy as described in the *Methods* section, part E, in order to investigate the generalizability of the training set as a function of the number of training positions in the set.

Notice that the classification error improvement when increasing the number of training positions from one to two is larger than when increasing to three or four training positions.

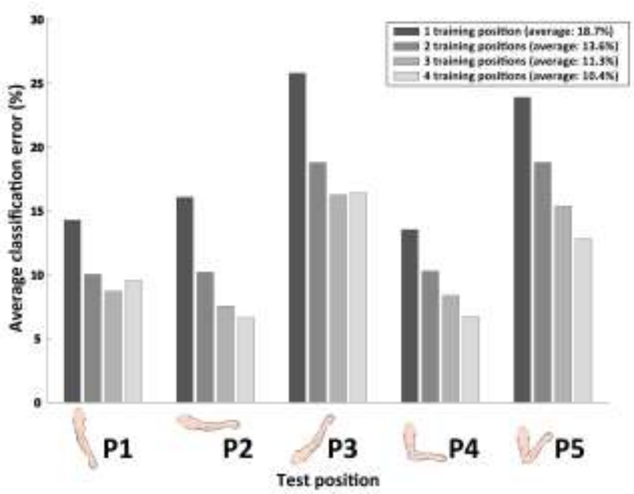

Fig. 2: Comparison of classification errors when testing in one limb position and training in all possible subsets of the remaining positions (the "Leave-one-out" strategy, as described in the Methods section, part E). Note that the training sets have been scaled so that they have identical size every time; independently of the number of training positions, by using subsets of the ten trials.

C. Relative importance of position information and surface EMG

The results of the input selection described in the *Methods* section, part F, are presented in Fig. 3. It is noteworthy that when adding new sensors one by one, the forearm accelerometer provides more novel classification information than even a second or third EMG electrode. It is also worth noting that the upper arm accelerometer is one of the least useful sensors. This is a desirable result as it would be difficult to justify including a sensor external to the forearm socket, and across the elbow joint.

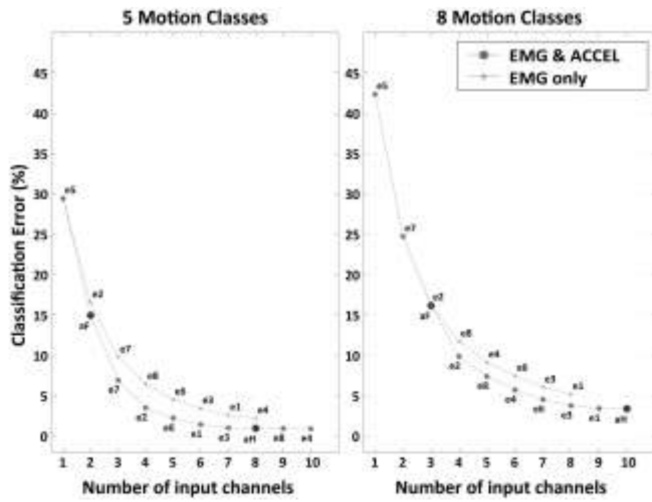

Fig. 3: Classification error as a function of selected input channels, for pattern recognition systems with 5 and 8 motion classes, choosing input channels among 8 electrode pairs (e1–e8) and 2 accelerometers (aF–Forearm, aH–Humerus).

For the *contemporary* system, the improvement flattens out after 4-5 electrodes and one forearm accelerometer (reaching an average accuracy of 98-99%). The advanced system can exploit 6-7 electrodes and one forearm accelerometer (reaching an average accuracy of 95-96%).

DISCUSSION

EMG TD features and training an LDA classifier in in a single limb position yielded an average intra-position error (3.8%) significantly lower than the corresponding inter-position errors (21.1%). These results indicate that EMG classification error is strongly dependent on limb position.

We have shown that the limb position effect can be partially solved by training the classifier in multiple positions. Since training in multiple positions can be cumbersome for the end user, it is however desirable to reduce the number of training positions. Therefore it is an advantage that most of the improvement is achieved already when increasing from one to two training positions (reducing the average error from 18.7% to 13.6%).

Previously we have also shown [10] that that it is important to have a training set containing a variation of elbow angle.

The accelerometer lends itself to being used in human-machine interfaces due to its small size, low cost, and simple mechanical and electrical interfaces. The absence of many of the disturbances often encountered in EMG sensors and similar devices makes it interesting as a supplementary sensor in hand motion classification systems, including upper limb prostheses.

The accelerometer does not provide an estimate of muscle force, but we have shown that it provides useful information that can supplement EMG signals. If one wants to improve a system originally having two EMG electrodes, a multi-modal approach can be taken. The results demonstrate that it is more advantageous to add an accelerometer affixed to the forearm (multi-modal approach) rather than increase the number of EMG channels (uni-modal approach).

Even though the limb position effect was discovered and observed in users in the clinic [7],[10], and was resolved for the normally limbed subjects in our study, it needs to be examined specifically for the end users. Gravitational and biomechanical effects of limb position will be different for prosthetic users compared to the normally limbed subjects of this study. As such, we are planning to extend this study to include prosthesis users.

This work is part of a larger investigation aimed at improving the practical robustness of myoelectric control. The present results 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 larger work.

ACKNOWLEDGEMENTS

The authors would like to thank P. J. Kyberd for important input concerning the experimental protocol and invaluable practical assistance in conjunction with the accelerometers.

The work was supported in part by NSERC Discovery Grant 217354-10, NIH Grant 5R01HD058000-03, the Atlantic Innovation Fund, Strategic Area Medical Technology at NTNU and The Research Council of Norway (Grant 192546).

REFERENCES

[1] L. P. J. Kenney, I. Lisitsa, P. Bowker, G. H. Heath, and D. Howard, “Dimensional Change in Muscle as a Control Signal for Powered Upper Limb Prostheses: a Pilot Study”, *Med. Eng. Phys.*, 21(8):589–597, Oct. 1999.

[2] J. Canderle, L. P. J. Kenney, A. Bowen, D. Howard, and H. Chatterton, “A Dual-task Approach to the Evaluation of the Myokinemetric Signal as an Alternative to EMG”, Conf. *Proc. IEEE Eng. Med. Biol. Soc*. 2004, 26:4548–4551, Sep. 2004.

[3] E. M. Scheeren, E. Krueger-Beck, G. Nogueira-Neto, P. Nohama, and V. L. S. N. Button, “Wrist Movement Characterization by Mechanomyography Technique”, *J. Med. Biol. Eng.*, 30(6):373–380, Dec. 2010.

[4] M. E. Harrington, R. W. Daniel, P. J. Kyberd, “A Measurement System for the Recognition of Arm Gestures using Accelerometers”, *Proc. Inst. Mech. Eng. Part H: J. Eng. Med.*, 209(H2):129–134, 1995.

[5] L. J. Hargrove, K. Englehart, B. Hudgins, “A Comparison of Surface and Intramuscular Myoelectric Signal Classification”, *IEEE Trans. Biomed. Eng.*, 54(5):847–853, May 2007.

[6] A. Fougner, M. Sæther, Ø. Stavdahl, J. Blum, P. J. Kyberd, “Cancellation of Force Induced Artifacts in Surface EMG Using FSR Measurements”, *Proc. of Myoelectric Controls Symposium (MEC) 2008*, pp. 146–149, Aug. 2008.

[7] E. Scheme, A. Fougner, Ø. Stavdahl, A. D. C. Chan, K. Englehart, “Examining the Adverse Effects of Limb Position on Pattern Recognition Based Myoelectric Control”, *Conf. Proc. IEEE Eng. Med. Biol. Soc.* 2010, 32:6337–40, Sep. 2010.

[8] A. D. C. Chan, K. Englehart, B. Hudgins, and D. F. Lovely, “Multi-expert automatic speech recognition using acoustic and myoelectric signals”, *IEEE Trans. Biomed. Eng.*, 53(4):676–685, Apr. 2006.

[9] B. Duc, E. S. Bigun, J. Bigun, G. Maitre, and S. Fischer, “Fusion of Audio and Video Information for Multi-Modal Person Authentication,” *Pattern Recognit. Lett.*, 18(9):835–843, Sep. 1997.

[10] A. Fougner, E. Scheme, A. D. C. Chan, K. Englehart, and Ø. Stavdahl, “Resolving the Limb Position Effect in Myoelectric Pattern Recognition”, *IEEE Trans. Neural Syst. Rehabil. Eng.*, submitted for publication.

[11] K. Englehart and B. Hudgins, “A Robust Real-time Control Scheme For Multifunction Myoelectric Control”, *IEEE Trans. Biomed. Eng.*, 50(7):848–854, Jul. 2003.

[12] H. Bouwsema, C. K. van der Sluis, and R. M. Bongers, “Learning to Control Opening and Closing a Myoelectric Hand”, *Archives of Physical Medicine and Rehabilitation,* 91(9):1442–1446, Sep. 2010.