Resolving the Limb Position Effect in Myoelectric Pattern Recognition

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***Abstract*—Reported studies on pattern recognition of electromyograms (EMG) for the control of prosthetic devices traditionally focus on classification accuracy of signals recorded in a laboratory. The difference between the constrained nature in which such data are often collected and the unpredictable nature of prosthetic use is an example of the semantic gap between research findings and a viable clinical implementation.**

In this work, we demonstrate that the variations in limb position associated with normal use can have a substantial impact on the robustness of EMG pattern recognition, as illustrated by an increase in average classification error from 3.8% to 18%.

We propose to solve this problem by (1) collecting EMG data and training the classifier in multiple limb positions and by (2) measuring the limb position with accelerometers. Applying these two methods to data from ten normally limbed subjects, we reduce the average classification error from 18% to 5.7% and 5.0%, respectively.

Our study shows how sensor fusion (using EMG and accelerometers) may be an efficient method to mitigate the effect of limb position and improve classification accuracy.

***Index terms*—Accelerometer, prosthetics, prosthetic hands, electromyography.**

I. INTRODUCTION

THERE is a significant body of research describing the use of pattern recognition of myoelectric signals to control prosthetic devices [1]-[7]. A large majority of this work focuses mainly on improving the offline classification accuracy of pre-recorded signals. While the results of these works are important, they fail to address what may be described as a semantic gap between research findings and a viable implementation. A study by Hill *et al.* [8] puts this into the context of the World Health Organization International Classification of Function (ICF) [9]. While most prosthetics research is done in the *Function* domain in a laboratory, it should also be tested in the *Activity* domain in the clinic, and at the final stage in the *Participation* domain by the end user.

In order to bridge this gap, it is important to examine the source of the disparity between current research and clinical results. One difference relates to the way that electromyogram (EMG) data are acquired for conventional offline classification. In research, for example, forearm EMG data are commonly acquired with the subject in a seated position, with the elbow resting on the arm of a chair. This is done because it makes it easier for the subject to perform repeatable contractions across trials, resulting in classification accuracies that may be unrealistically high. In a clinical implementation, training data may be collected in the same way but testing usually consists of more task oriented usage scenarios. This requires the user to not only produce coordinated contractions, but also to elicit those contractions in a wide variety of limb positions. When it comes to activities of daily living, the conditions become even more disparate. Consider, for example, the task of reaching for a glass in a cupboard, filling that glass with water, and then taking a drink. It quickly becomes apparent that the typical prosthetic user requires that the remnant and prosthetic limb operate in a multitude of positions.

Pattern recognition of EMG signals relies on the generation of differentiable and repeatable contractions. Changes in these patterns can erode the performance of the classifier and may result in an unusable controller. Such pattern alterations can occur for various reasons. Hargrove *et al.* [10] showed that electrode displacement, if unaccounted for during training, could degrade pattern recognition performance. Findings by Howard *et al*. [11] and Jamison and Caldwell [12] indicate that some muscles' activity depends on the angles in joints other than those primarily actuated by these muscles. Changes in the shape and length of muscles caused by limb positioning can result in a shift between the signal source and electrode, but even the muscle lengthening will change the efficiency of the muscle due to the degree of overlap of thin and thick filaments, causing an associated change in EMG activity [13].

Manuscript received January 15, 2011. This 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).

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The inspiration for this study is based on clinical observations made during training sessions with amputee patients. A severe degradation in pattern recognition performance has been subjectively linked to changes in posture and limb position. In this work, we investigate the effect of changing limb position on classification accuracy. In addition, we propose two possible solutions to reduce the adverse *limb position effect*:

1) *Training in multiple limb positions* – By training in multiple positions, we inform the pattern recognition system of what the patterns are like in each single position. This expands the boundaries of each class to include the effects of position variation.
2) *Measuring the position* – This allows the pattern recognition system to know the position/orientation of the limb. With knowledge of position, a classifier can compensate for the effect on the EMG, or a position-specific classifier may be selected. We have used accelerometers to measure the static orientation of the forearm and the upper arm with respect to gravity.

The combination of EMG and accelerometers has previously been used by Roy *et al.* [14] for monitoring patients with stroke and by Li *et al.* [15] for sign language detection and game control. To the best of our knowledge the combination of EMG and accelerometers has not been used in conjunction with prosthesis control. This study is an example of a general trend towards including more sensor types to maximize the environmental and intent information provided to the control system. The pilot study for this work was described by Scheme *et al.* [16].

II. 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. The experience level in EMG-based motion classification ranged from none to moderate.

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 and the second was placed over the biceps brachii. The experimental setup is illustrated 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.

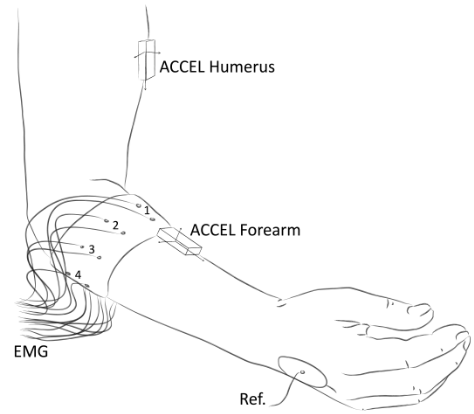

Fig. 1. Placement of electrodes and accelerometers.

Subjects were prompted to elicit contractions corresponding to the eight classes of motion shown in Fig. 2.

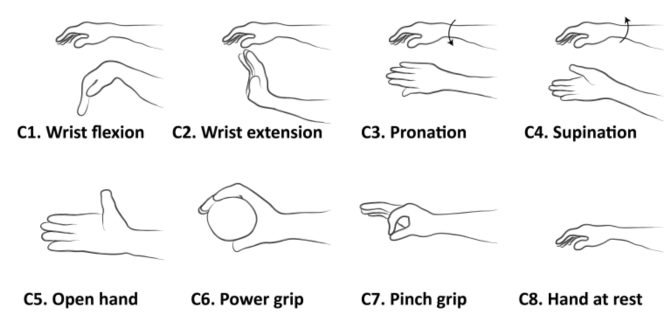

Fig. 2. Motion classes.

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. 3), resulting in a total data set of [*n* subjects × 10 trials × 5 positions × 8 classes × 3 seconds], where *n* is explained in Section C.

- **P1.** Straight arm hanging at side.
- **P2.** Straight arm reaching forward (horizontal).
- **P3.** Straight arm reaching up (45° from vertical).
- **P4.** Humerus hanging at side, forearm horizontal.
- **P5.** Humerus hanging at side, forearm 45° above horizontal.

Fig. 3. Limb positions (illustration inspired by A. Loomis' drawings [15]).

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 subjects noted minor shoulder (deltoid) fatigue.

B. Data processing

As this work represents an introductory look at the effect of position on pattern recognition, it was appropriate to test the effects using a known control scheme. Englehart and Hudgins [1] 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. Four TD features (mean absolute value, zero crossings, number of turns and waveform length) were extracted from the EMG data. Feature selection is not in focus of our study. Please refer to [1] 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 fed into 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 myoelectric signals [19]. 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. However, the corresponding EMG data were consistent and could be used for some parts of the study. In the following, the inclusion or exclusion of the two subjects with erroneous accelerometer data are indicated by numbers of subjects $n = 12$ or $n = 10$, respectively.

D. Classification

All classifiers were trained using data from the first five trials and tested using data from the last five trials, unless otherwise stated. Training was always done individually for each subject.

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 ($n = 12$).

2) *Training in multiple limb positions*
TD features recorded in multiple limb positions were concatenated and used to train the classifier ($n = 12$).

3) *Two-stage position-aware classification*
One motion classifier was trained in each position. For testing, the following stages were used:
   - *Limb position detection.* Accelerometer data were used for limb position classification ($n = 10$). For these subjects a zero position classification error was demonstrated (see Fig. 8). This result justifies the assumption of perfect position classification in the following stage.
   - *Position specific motion classification.* Perfect position classification was assumed (that is, the correct motion classifier was always used). TD features were used for position specific motion classification ($n = 12$).

4) *Single-stage position-aware classification*
TD and ACCEL features recorded in multiple positions were concatenated to form feature vectors:

$$\begin{bmatrix} \{\mathrm{TD}_{i,j}\}\Big|_{i=1\ldots4,\ j=1\ldots8} \\ \{\mathrm{ACCEL}_{k,l}\}\Big|_{k=1\ldots2,\ l=x\ldots z} \end{bmatrix} \text{ where } \begin{matrix} i\text{: feature no.} \\ j\text{: electrode no.} \\ k\text{: accel. no.} \\ l\text{: axis label} \end{matrix} \qquad (1)$$

The feature vectors were then used for motion classification ($n = 10$).

III. 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 matrix of inter-position errors is shown in Fig. 4. Each entry in the matrix represents the average error of all motion classes across all subjects for the indicated training and test positions (vertical and horizontal axis, respectively). The classification errors shown in the main diagonal represent the intra-position classification errors, while the off-diagonal elements represent the inter-position errors.

The mean intra-position classification error (on the diagonal) was 3.8%, whereas the mean inter-position error was 21.1% and the mean overall error was 17.6%.

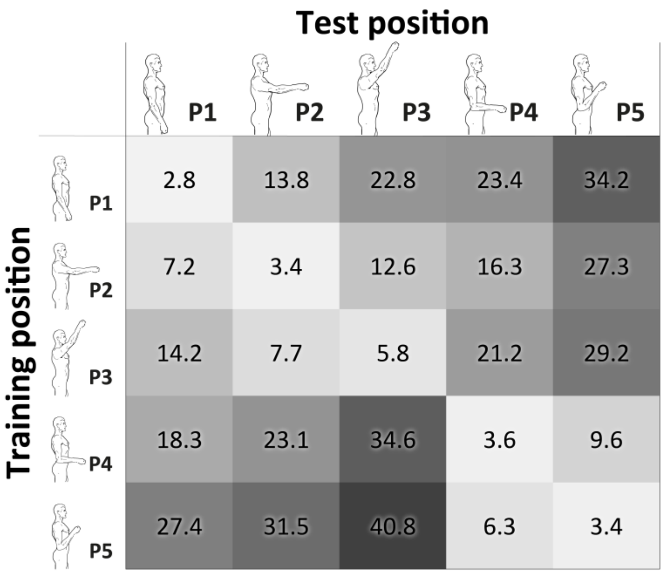

Fig. 4. Inter-position classification error (in %), averaged across all subjects and classes. Darker shades indicate greater error.

Fig. 5 illustrates the class-specific limb position effect, using a similar confusion matrix. It illustrates the same results as those in Fig. 4, but they are averaged across positions instead of classes.

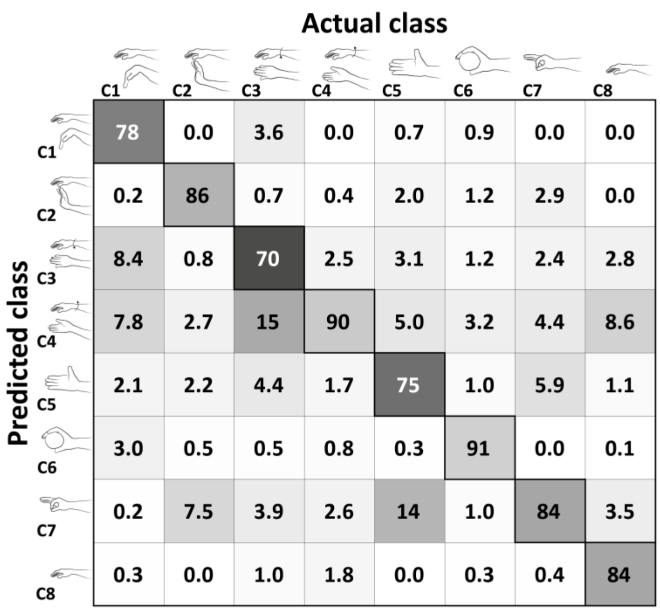

Fig. 5. Confusion matrix (in %), averaged across all subjects and positions. The classifier was based on EMG input and training in a single position. The color coding of the main diagonal entries has been inverted, so that a perfect classification result would yield 100% on the diagonal and 0% everywhere else, and a completely white matrix (rounding errors may yield column sums not identical to 100).

For a closer look at how the position affects the discrimination of specific classes, the inter-position classification matrix in Fig. 4 is broken out into class specific matrices in Fig. 6.

The motion classes that are most influenced by limb position can been identified in Fig. 5 as dark-colored elements off of the main diagonal. The discrimination of these classes is exacerbated by some positions more than others (Fig. 6). An example of this is the discrimination of Class 3 (Wrist Pronation), which is severely affected by changes in elbow angle, i.e. when training with flexed elbow and testing with extended elbow or vice versa. Similarly, the results for Class 8 (Hand at rest) are poor in Position 3 (Reaching up) when trained in another position.

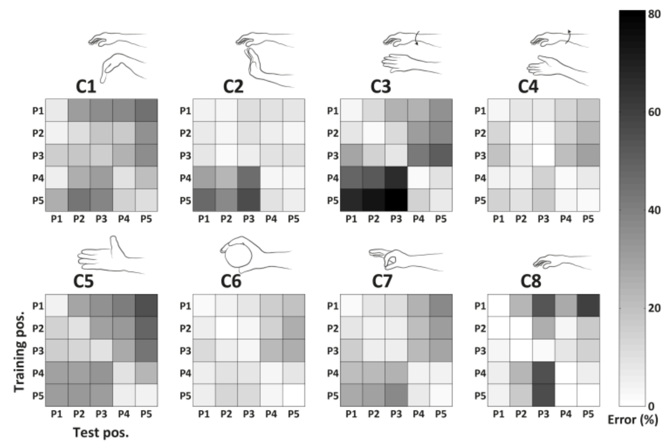

Fig. 6. Inter-position classification error (in %), averaged across all subjects and shown separately for each class.

B. *Training in multiple limb positions*

The average classification errors when using data from multiple (1-5) positions in the training set and all five positions in the test set were calculated and are presented in Fig. 7.

It is interesting to note that the elbow is extended in P1-P3, while it is flexed in P4 and P5. For the sake of comparison we have divided the training set combinations into two groups: *Group 1* consists of the training set combinations corresponding to both a flexed elbow and an extended elbow. *Group 2* consists of the combinations corresponding to only one of these cases. The results imply that the training set combinations in *Group 1* perform better than those in *Group 2*. The median classification errors of the two groups are significantly different ($p<0.005$) according to the Kruskal-Wallis test [18],[20]. This implies that including variations in elbow angle is an important aspect of multi-position training.

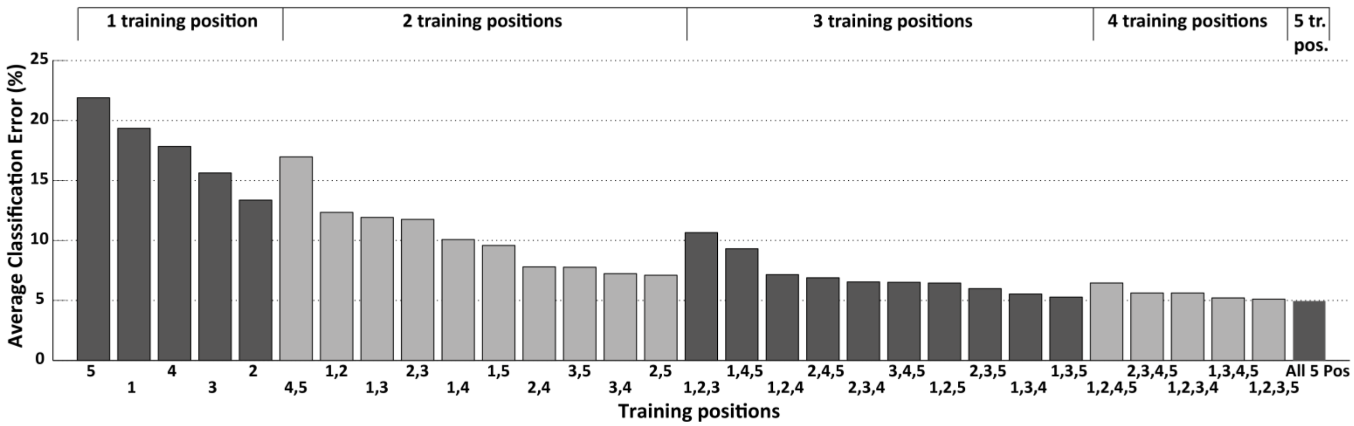

Fig. 7. Classification errors when training in each combination of position subsets and testing in all 5 positions. The result is averaged over all subjects, classes and test positions. The error bars represent the standard deviation across test positions.

C. *Two-stage position aware classification*

1) *Limb position detection*

The results of limb position classification using accelerometer data are illustrated in Fig. 8. Note that the classifier was able to identify position with zero error when using the ACCEL features from both accelerometers, thus the corresponding bars are not visible in the figure.

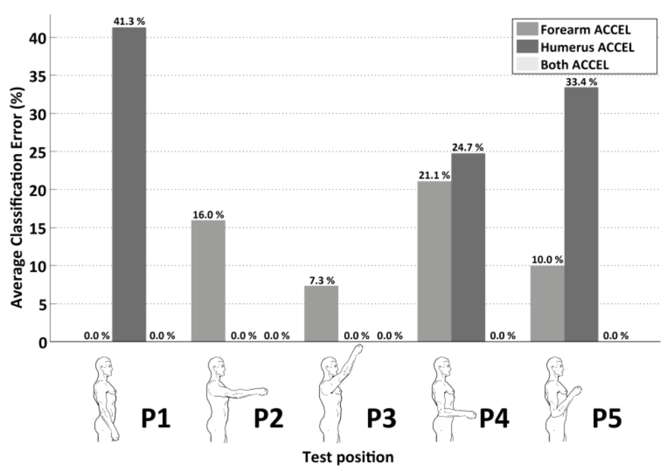

Fig. 8. Classification error of limb position when using accelerometer data. The results are averaged across all subjects and classes.

2) *Position-specific motion classification*

Assuming known positions, a position specific motion classifier was trained. The results are presented in Fig. 9 along with the results of the classifier from *Results* section *A* (trained in a single position, P4, using TD features only) and a classifier from *Results* section *B* (trained in multiple positions, using TD features only).

The two-stage position-aware classifier had an average error across all subjects and test positions of 3.8% while the classifier trained only with TD features from multiple positions had a 4.9% error and the classifier trained only in a single position (P4) had a 17.8% error.

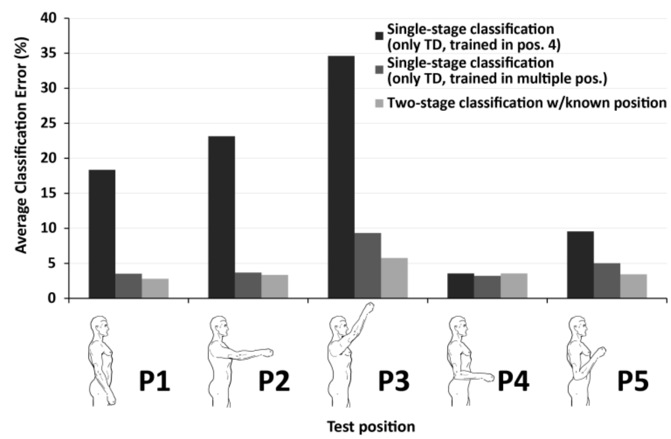

Fig. 9. Comparison of a classifier trained only in position 4 (the normal approach) with a single-stage classifier trained in multiple positions and a two-stage classifier using known position. The classification error values are averaged across all subjects and classes.

D. *Single-stage position-aware classification*

The results of a single-stage motion classifier using ACCEL features from one or two accelerometers in addition to the TD features are illustrated in Fig. 10. For comparison, we have also included the results of using only TD features.

The results of using only the upper arm accelerometer are omitted in the figure; since they skewed the scale of the axes (they were much worse than the results for other methods).

Our results show that the accelerometers can improve the system, but only the forearm accelerometer is needed to get this improvement. We can also see that the single-stage classifier performs better than the two-stage classifier.

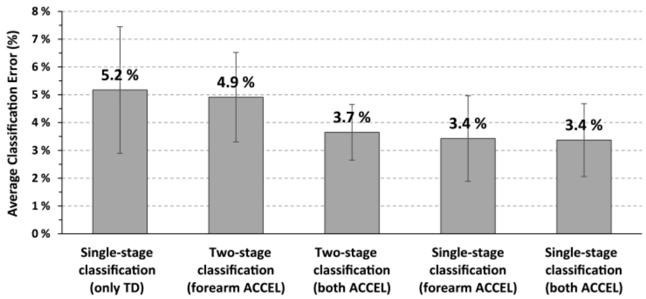

Fig. 10. Comparison of classification based only on EMG TD features with four methods based on TD and ACCEL features. The bars represent the value averaged across all subjects and test positions, and the standard deviation is computed over test positions (i.e. averaged over subjects).

All three single-stage classification schemes are presented in Fig. 11, comparing our methods with the standard approach of training in a single position and using TD features of EMG only. The numbers are omitted for clarity. However, as an example the misclassification of Class 3 (Pronation) as Class 4 (Supination), i.e. row 4/column 3, happens in 16.9% of the cases when training in a single position with TD features. By training in multiple positions, this misclassification was reduced to 3.7%, and by using ACCEL features along with TD it was reduced to 0.6%.

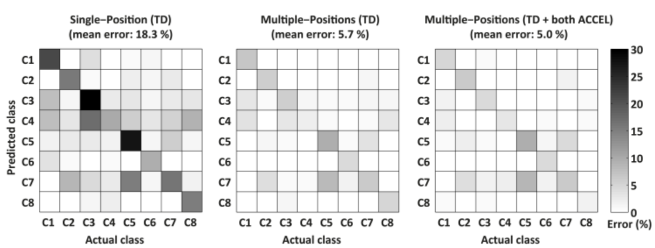

Fig. 11. Comparison of training in a single position (TD), training in multiple positions (TD) and training in multiple positions (TD + both ACCEL). These confusion matrices are made in the same way as Fig. 5, i.e. with inverted colors on the diagonal. For the case of multiple training positions, the training set size was scaled to the same size as for single-position, by using only one trial instead of five.

IV. Discussion

EMG TD features and training in a single position yielded an average intra-position classification error (3.8%) significantly lower than the corresponding inter-position errors (21.1%). The 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 due to gravitational forces), electrode shift (due to changes in muscle shape, length and position), the force-length relationship of the muscle, and changes in the musculotendon lever arm, which all depend on joint angles. As a result, training a prosthetic control system in a single position may be insufficient if the system is to perform well in multi-position use. The degradation shown when changing between positions may contribute to the differences seen between published classification accuracy results and observed clinical performance.

Some subjects noted minor shoulder (deltoid) fatigue. The effect of the fatigue on accuracy is expected to be negative. Although fatigue was not the focus of this work, the manifestation of fatigue effects in the EMG is a reality of prosthetic usage. In these experiments, the effect of limb position appears to be more dominant than any fatigue effect that may have occurred.

By training in multiple positions, the overall classification error was reduced substantially (from 17.6% to 4.9%, Fig. 9). Since training in multiple positions can be cumbersome for the end user, it is desirable to reduce the number of training positions. We have shown that the performance improvement decreases with each additional position. For a test set of five positions, an increase from three to five training positions only yields a reduction from 5.3% to 4.9% in the associated classification error. We have also shown that it is important to have a training set containing a variation in elbow angle. It remains to investigate how many, and which, training positions will be needed for the prosthesis users, since it is desirable to reduce the training time.

A limb position classifier using ACCEL features was able to detect the static position with zero error (Fig. 8). Position specific motion classifiers were then used to reduce the overall motion classification error from 5.2% to 3.7% (Fig. 9 & Fig. 10). By using the ACCEL features as an additional input to a single-stage motion classifier trained in multiple positions, the error was further reduced to 3.4%. It is hypothesized that the single-stage method had better performance than the two-stage method because, in the latter case, the limb position classifier abstracts the ACCEL data to a discrete limb position, thereby reducing the information content.

It was shown that the forearm accelerometer is sufficient to achieve an improvement in the single-stage motion classifier (overall motion classification error of 3.4%). With both accelerometers, the same average performance was achieved but with lower variability among subjects; however, the use of the single forearm accelerometer simplifies the task of implementing this method in existing prostheses. While a forearm accelerometer can be built into a transradial prosthesis socket, an upper arm accelerometer would need to be external to the socket, complicating the fitting process.

According to Hill *et al.* [8], the domains *Function*, *Activity* and *Participation* can be related to the situations *Research*, *Development*, *Clinical Assessment* and *Daily Use*. The corresponding progression, when it comes to myoelectric pattern recognition control, can be identified as that from single-position pre-recorded data with off-line classification to general dynamic movements. As illustrated in Table 1, our study represents a shift from *Function* towards the *Activity* domain by taking multiple limb positions into account. Nonetheless, there is clearly still a significant amount of work that needs to be done to extend this research to the *Participation* domain and hence *Daily Use*.

Table 1. Domains, situations and positions in myoelectric pattern recognition

<table>
<tr><th>Function</th><th colspan="2">Activity</th><th>Participation</th></tr>
<tr><td>Research</td><td>Development</td><td>Clinic</td><td>Home</td></tr>
<tr><td>Single position</td><td colspan="2">Multiple static pos.</td><td>Dynamic use</td></tr>
</table>

Recently, renewed international interest towards advancing prosthetics research has pushed the field to provide more clinically relevant outcome measures. In the present study, we have adopted the traditional classification accuracy as our outcome measure. However, Lock et al. [21] showed only a very weak correlation between classification accuracy and usability. Hargrove et al. [22] found that by including transient contractions in their training data, they could simultaneously improve the results of a virtual clothespin placement task and decrease standard classification accuracy. Kuiken et al. [23] introduced alternative quantitative usability metrics focused on class selection and motion completion times. This kind of outcome measure is needed to further assess the validity of these results in the *Activity* domain and beyond.

Gravitational and biomechanical effects of limb position will be different for prosthesis users compared to the normally limbed subjects of this study. It is an open question whether the position effect will be smaller or larger. Although a residual limb is shorter and lighter than a healthy one, the influence of gravity on the EMG signals may still be larger due to the shorter residual that is to take the gravitational load of the prosthesis. Also, when wearing a prosthesis socket, the effect of position will manifest itself in other ways, such as changes in contact forces between the socket and the skin, which will likely produce changes in EMG patterns in a manner not represented in our present data. Likewise, the biomechanical effects in the prosthetic case are still to be researched. Nevertheless, since our study was inspired by clinical observations made during sessions with amputee patients, we believe that it is relevant also for them.

V. Future work

The present results show that our methods are applicable to upper-limb movement pattern recognition in able-bodied subjects, and as such may find immediate usage in applications such as sign language recognition and the study of musical gestures. The results also are an encouraging starting point for adapting the methods to be used in prosthesis control. The population of prosthesis users is limited, so for practical and ethical reasons the present method assessment using able-bodied subjects represents a necessary first step towards this ultimate goal. The next step will be to validate the results by application to prosthesis users.

The mitigation techniques discussed here all require collection of training data in multiple positions. This may prove to be cumbersome for the end prosthetic user, and therefore, an ideal controller would provide position invariant control after being trained in a single position. While we have shown that training in only a subset of position yields positive results, we have yet to attain this goal.

While the accelerometers are able to give information about a limb's orientation, they can also be used to measure the dynamical movements of the limb. In the case of simultaneous proportional control systems, such as those described by Jiang [24] and Fougner [25], they could be even more useful.

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.

VI. Acknowledgments

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.

VII. References

[1] 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.

[2] G. N. Saridis and T. P. Gootee, "EMG Pattern Analysis And Classification For a Prosthetic Arm", *IEEE Trans. Biomed. Eng.*, 29(6):403–412, Jun. 1982.

[3] P. Parker, K. Englehart, and B. Hudgins, "Myoelectric Signal Processing For Control of Powered Prosthesis", *J. Electromyogr. Kinesiol.*, 16(6):541–548, Dec. 2006.

[4] Y. Huang, K. Englehart, B. Hudgins, and A.D.C. Chan, "A Gaussian Mixture Model Based Classification Scheme For Myoelectric Control of Powered Upper Limb Prostheses", *IEEE Trans. Biomed. Eng.*, 52(11):1801–1811, 2005.

[5] A.D.C. Chan and K. Englehart, "Continuous Myoelectric Control for Powered Prostheses Using Hidden Markov Models", *IEEE Trans. Biomed. Eng.*, 52(1):121–124, 2005.

[6] W. J. Kang, J. R. Shiu, C. K. Cheng, J. S. Lai, H. W. Tsao, and T. S. Kuo, "The Application of Cepstral Coefficients and Maximum Likelihood Method in EMG Pattern Recognition", *IEEE Trans. Biomed. Eng*., 42(8):777–785, Aug. 1995.

[7] P. J. Gallant, E. L. Morin, and L. E. Peppard, "Feature-Based Classification of Myoelectric Signals Using Artificial Neural Networks", *Med. Bio. Eng. Comp.*, 36(4):485–489, Jul. 1998.

[8] W. Hill, Ø. Stavdahl, L. N. Hermansson, P. Kyberd, S. Swanson, S. Hubbard, "Functional Outcomes in the WHO-ICF Model: Establishment of the Upper Limb Prosthetic Outcome Measures Group", *J. Prosthet. Orthot.*, 21:115-119, 2009.

[9] World Health Organization, "Towards a Common Language for Functionary, Disability and Health: ICF Beginner's Guide" (WHO/EIP/GPE/CAS/01.3), Geneva, 2002.

[10] L. Hargrove, K. Englehart and B. Hudgins, "A Training Strategy to Reduce Classification Degradation Due to Electrode Displacements in Pattern Recognition Based Myoelectric Control", *Biomed. Signal Process. Contr.*, 3(2):175–180, 2008.

[11] J. D. Howard, J. D. Hoit, R. M. Enoka, and Z. Hasan, "Relative Activation of Two Human Elbow Flexors

Under Isometric Conditions: A Cautionary Note Concerning Flexor Equivalence", *Exp. Brain Res.*, 62(1):199–202, 1986.

[12] J. C. Jamison and G. E. Caldwell, "Muscle Synergies and Isometric Torque Production: Influence of Supination and Pronation Level on Elbow Flexion", *J. Neurophys.*, 70(3):947–960, 1993.

[13] D. T. MacIsaac, P. A. Parker, R. N. Scott, K. Englehart, and C. Duffley, "Influences of Dynamic Factors on Myoelectric Parameters", *IEEE Eng. Med. Biol.*, 20(6):82–89, Nov 2001.

[14] S. H. Roy, M. S. Cheng, S. Chang, J. Moore, G. De Luca, S. H. Nawab, and C. J. De Luca, "A Combined sEMG and Accelerometer System for Monitoring Functional Activity in Stroke", *IEEE Trans. Neural Syst. Rehabil. Eng.*, 17(6):585–594, Dec. 2009.

[15] Y. Li, X. Chen, J. Tian, X. Zhang, K. Wang, and J. Yang, "Automatic Recognition of Sign Language Subwords based on Portable Accelerometer and EMG Sensors", ICMI-MLMI'10, Beijing, China, Nov. 2010.

[16] 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.

[17] A. Loomis, *Figure Drawing For All It's Worth*, Walter Foster Publishing Inc., 1943.

[18] W. Kruskal and W. A. Wallis, "Use of Ranks in One-Criterion Variance Analysis", *J. Am. Stat. Assoc.* 47(260):583–621, Dec. 1952.

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

[20] B. Rosner, *Fundamentals of Biostatistics*, 7th edition (international edition), Boston, MA: Wadsworth, 2011, pp. 555–561.

[21] B. A. Lock, "Design and Interactive Assessment of Continuous Multifunction Myoelectric Control Systems", *Master's Thesis*, University of New Brunswick, Fredericton, New Brunswick, 2005.

[22] L. Hargrove, Y. Losier, B. Lock, K. Englehart, and B. Hudgins, "A Real-Time Pattern Recognition Based Myoelectric Control Usability Study Implemented in a Virtual Environment", in *Eng. Med. Biol.*, pp. 4842–4845, Lyon 2007.

[23] T. Kuiken, G. Li, B. Lock, R. Lipschutz, L. Miller, K. Stubblefield, and K. Englehart, "Targeted Muscle Reinnervation for Real-time Myoelectric Control of Multifunction Artificial Arms", *J. Am. Med. Assoc.*, 301(6):619–628, 2009.

[24] N. Jiang, K. Englehart, and P. A. Parker, "Extracting Simultaneous and Proportional Neural Control Information for Multiple-DOF Prostheses From the Surface Electromyographic Signal", *IEEE Trans. Biomed. Eng.*, 56(4):1070–1080, 2009.

[25] A. Fougner, "Proportional Myoelectric Control of a Multifunction Upper-Limb Prosthesis", *Master's Thesis*, Norwegian University of Science and Technology, Trondheim, Norway, Jun. 2007.

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