Published in final edited form as:

J Prosthet Orthot. 2013 April 1; 25(2): 76–83. doi:10.1097/JPO.0b013e318289950b.

Training Strategies for Mitigating the Effect of Proportional Control on Classification in Pattern Recognition Based Myoelectric Control

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Abstract

The performance of pattern recognition based myoelectric control has seen significant interest in the research community for many years. Due to a recent surge in the development of dexterous prosthetic devices, determining the clinical viability of multifunction myoelectric control has become paramount. Several factors contribute to differences between offline classification accuracy and clinical usability, but the overriding theme is that the variability of the elicited patterns increases greatly during functional use.

Proportional control has been shown to greatly improve the usability of conventional myoelectric control systems. Typically, a measure of the amplitude of the electromyogram (a rectified and smoothed version) is used to dictate the velocity of control of a device. The discriminatory power of myoelectric pattern classifiers, however, is also largely based on amplitude features of the electromyogram. This work presents an introductory look at the effect of contraction strength and proportional control on pattern recognition based control. These effects are investigated using typical pattern recognition data collection methods as well as a real-time position tracking test. Training with dynamically force varying contractions and appropriate gain selection is shown to significantly improve ($p < 0.001$) the classifier's performance and tolerance to proportional control.

Keywords

prosthetics; myoelectric control; EMG; proportional control; pattern recognition

INTRODUCTION

Myoelectric control has been used as a prosthetic control strategy for many years. Its popular usage dates back to the 1960s and 1970s.^{1–4} The most straightforward approaches use an estimate of the intensity of the myoelectric signal acquired from one or two surface electrodes placed over distinct remaining muscle sites. In many cases these intensities are mapped (through various control schemes) to control the speed of the prosthesis. This gives rise to proportional control of the device by varying contraction strength. The optimal method of deriving these proportional control signals was investigated in the 1980s,^{5–6} with a simple low-pass rectification approach eventually being widely adopted. Since then, the

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ability to control the rate of motion has been suggested to increase the usability of prosthetic devices, but little work has been published to quantify this.⁷⁻⁹ Consequently, references to myoelectric control in the literature often contain the wording “proportional myoelectric control” regardless of their attention to proportionality. More recently, several groups have looked at using force mapping techniques to elicit proportional and simultaneous control, but these techniques are still very new.¹⁰⁻¹²

Pattern recognition based approaches to myoelectric control have also been proposed for many years and, while still in the transition to clinical acceptance, they have found great traction in the research community.¹³ Improving the classification accuracy of these systems has been the primary focus and so pre-processing and pattern recognition techniques have dominated the literature. It was not until more recently that a shift in focus towards clinical viability began to expand the scope of the research.¹⁴ In 2005, Lock et al. showed that classification accuracy was not wholly indicative of usability.¹⁵ Deficiencies in clinical robustness have been speculatively linked to several factors, including socket fitting issues, temporal changes in signals, and an increase in variability of the signals during active prosthetic use. It is this induced variability that is of interest in the current work. Scheme et al. showed that, if left untreated, variations in limb position greatly affected classification accuracy.¹⁶⁻¹⁷ Hargrove et al. examined the effect of electrode shift and rotation, finding similar results.¹⁸⁻²⁰

With all the attention that pattern recognition based myoelectric control has garnered, there has been little reference to its use with proportional control. In practice, the proportional control signal is often derived from a simple weighted average of the mean absolute value (MAV) of the EMG channels used for pattern recognition. In 2011, Simon et al. were the first to compare this method with conventional direct proportional control and binary on/off pattern recognition control.²¹ They, however, did not address the interaction between proportional control and classification accuracy. In Hudgins et al.’s influential paper describing a novel myoelectric control scheme, they presented a time-domain set of features for classification that has since been widely adopted in myoelectric control research.²² It can be shown that the discriminatory power of these features predominantly comes from the MAV amplitude feature. As previously stated, the MAV is also used to derive the proportional control signal. This suggests that, while variations in contraction strength can be used to control proportionality, it may be to the detriment of the pattern classification.

In this work, the interaction between proportional control and classification accuracy is illustrated. With the goal of providing a control experience with high usability, best practices in proportional control gain selection and training methods have been developed.

METHODS

EMG data corresponding to seven classes of motion were collected from 10 healthy normally limbed subjects (7 male, 3 female) ranging in age from 25 to 50 years. Data were collected over two different sessions, conducted on separate days. All experiments were approved by the University of New Brunswick’s Research Ethics Board.

Subjects were fitted with a cuff made of thermoformable gel that was embedded with eight equally spaced pairs of stainless steel dome electrodes. The cuff was placed around the right forearm (the dominant side for all participants), at approximately one-third of the length of the forearm, around the area of largest circumference. A reference electrode (RedDot by 3M) was placed over the back of the hand.

The eight channels of EMG were differentially amplified using remote AC electrode-amplifiers (BE328 by Liberating Technologies, Inc.), and low pass filtered at 450Hz with a

5th order Butterworth filter. Data were sampled with a sampling frequency of 1000Hz using a 16-bit analog-to-digital converter.

Subjects were prompted to elicit contractions corresponding to the seven classes of motion shown in Figure 1.

A. Data Acquisition: Session 1

Subjects were asked to perform three-second steady-state contractions of each motion shown in Figure 1 and were given a two-second rest period between each. Users were prompted to perform the contractions at the following different force levels.

- ✦ Two reps at a *medium* level, corresponding to a moderate proportional control velocity.
- ✦ Two reps at a *light* level, corresponding to a slow proportional control velocity.
- ✦ Two reps at a *hard* level, corresponding to a fast proportional control velocity.
- ✦ Two reps at *100%*, corresponding to a class-specific maximum voluntary contraction (MVC).

Note that while the subjects were instructed to elicit an intended force level, their interpretation of that level was determined subjectively without feedback. Following the collection of the 100% repetitions, successive reps were collected as a percentage of MVC, while providing real-time proportional control feedback. Users were asked to track specific amplitude targets corresponding to percentage levels of effort (normalized by their 100% class-specific levels). The collection order was randomized but included 2 reps each of:

- ✦ 20, 30, 40, 50, 60, 70 and 80% of MVC.
- ✦ A dynamic ramp from 20%-80% of MVC.

This entire process was then repeated (with the exception of the 100% reps) resulting in 4 reps of each level and a total of 46 reps of each motion class.

B. Data Acquisition: Session 2

As in *session 1*, subjects were asked to elicit the seven motions from Figure 1 at different force levels to be used as training data. This time, the users were prompted to perform the following reps without feedback, as they saw fit:

- ✦ Two reps at a *medium* level, corresponding to a moderate proportional control velocity
- ✦ Two reps of a *ramp*, dynamically increasing intensity from a *light* to a *hard* level

Upon completion of this training data collection, *session 2* consisted of a real-time tracking test, shown in Figure 2, similar to those used by Simon et al.²¹ and Corbett et al.²³ Users were instructed to use class-specific proportional position control to track a sinusoid of randomly varying height and frequency. The control output was low pass filtered at 15Hz to smooth the visualization (and to emulate the inertial smoothing effect incurred when driving mechanical devices). The target height was bound to the dynamic range of the control signal, and the target signal was band-limited to 10Hz to allow for theoretically perfect tracking. Because the target motion changed during the test the user was required to elicit the required proportional control output in the context of the target motion contraction. The users' reticle (shown as a red circle in Figure 2) was hidden when the user-elicited contraction was classified as something other than the target motion class.

The tracking test consisted of tracking each active motion (excluding no motion) for 10 seconds with a 4-second pause between classes. The test was conducted under varying combinations of two conditions:

1. Training data (*medium* or *ramp* reps).
2. Automatic gain selection.

Because the training and configuration of pattern recognition based systems can be cumbersome and complex, it is desirable to minimize the requirements. By automatically determining class-specific gains using the training data, the burden on the clinician and patient could be reduced. Herein, gain selection for the proportional control signal was done by auto-scaling the mean of the class-specific proportional control signal (calculated using data from the training reps) to seven different levels corresponding to 40%, 50%, 60%, 70%, 80%, 90% and 100% of the full dynamic range. This was done as follows:

$$MAV_{ij} = \frac{1}{N_j} \sum_{n=1}^{N_j} |x_{i,j}[n]| \quad (1)$$

where N_j is the number of samples for class j , $x_{i,j}$ is the data from channel i for class j , and MAV_{ij} is its mean absolute value. The class-specific mean proportional control value, PC_j , was calculated using:

$$PC_j = \frac{1}{N_i} \sum_{i=1}^{N_i} MAV_{ij} \quad (2)$$

where N_i is the number of channels of EMG used for pattern recognition. Finally, the class-specific gain was determined using:

$$\text{Gain}_j = \frac{T_L}{PC_j} \quad (3)$$

where T_L is the desired target level (as a percentage of full scale) to map the class-specific mean proportional control value to. During feed-forward use, the real-time proportional control value, PC_{cur} , was determined using:

$$PC_{cur} = \text{Gain}_{pr} \times \frac{1}{N_i} \frac{1}{N_f} \sum_{i=1}^{N_i} \sum_{n=1}^{N_f} |x_i[n]| \quad (4)$$

where Gain_{pr} is the class-specific gain for the current pattern recognition output, N_i is the number of channels, N_f is the frame length used for pattern recognition and x_i is the raw EMG data for channel i .

Three trials of the test were repeated for each combination of training data and gain setting, resulting in 42 total trials per subject.

C. Signal processing

Many different myoelectric control schemes have been proposed in the literature. The current ‘state-of-the-art’ is, debatably, based on the work of Englehart and Hudgins.²⁴ They showed that combining a linear discriminant analysis (LDA) classifier with time-domain (TD) features provided effective real-time myoelectric control. Because of its minimal processing requirements, its simplicity, and its favorable performance, this system has been widely adopted¹³ and was used in this work.

Sampled EMG data were notch filtered at 60 Hz using a 3rd order Butterworth filter and segmented for feature extraction using 160 ms windows, with processing increments of 16 ms. During the real-time tracking portion of Session 2, a 9-decision majority vote window was used to smooth intermittent decisions. This was done by overwriting the instantaneous output decision by the decision occurring most frequently during the previous nine outputs.

Results from *Session 1* were compared using standard classification error. In *Session 2*, performance during the real-time amplitude tracking test was evaluated using classification error and the R² error:

$$MAV_{ij=1} = \frac{\sum_{n=1}^N (\widehat{a[n]} - a[n])^2}{\sum_{n=1}^N (a[n] - \overline{a[n]})^2} \quad (5)$$

where $\widehat{a[n]}$ is the user generated amplitude, $a[n]$ is the target amplitude, and $\overline{a[n]}$ is the mean target amplitude.

The R² Statistical analyses were conducted using a multi-way ANOVA with a post-hoc multiple comparison (Tukey-Kramer) test. The alpha value used was 0.001.

RESULTS

A. Session 1: Inter- and intra-level analysis

A separate classifier was trained using data from each different contraction level (11 classifiers in total), and tested using data from all levels. Testing was repeated in a leave-two-out fashion, each time training with two reps and testing with the other two. The results were averaged and are shown in Table 1. Lower levels of error are shown as lighter colors, while higher errors are shown as darker colors. It can be seen that the intra-level errors (those on the diagonal) are lower, with a mean error of 9.3%, while the mean inter-level error is 31.2%. Of note is the mean inter-level error when training with a ramp contraction, which is 18.9%. This is lower than any other single level.

From Figure 3, it can be seen that increasing training contraction strength distances the features from the no motion data. Considering that the LDA classifier boundaries are determined using these training clusters, it is understandable how a classifier trained with, for example, the 80% clusters could erroneously misclassify data from the 20% clusters as no motion. Note that the ramp data largely encompass the areas ranging from the 20% to the 80% clusters and in between.

Figure 4 shows the results of a multi-way ANOVA when training with each single training level and testing with all levels. The results shown were calculated using a post-hoc multiple comparison test and showed a significant training effect ($p < 0.001$). The horizontal interval bars were computed using MATLAB's (© The MathWorks Inc.) *multcompare* function such that two estimates are significantly different if they have non-overlapping intervals. Note again that the ramp contraction significantly outperformed all other levels. It should be noted that, while combining multiple discrete training levels also performed well, collection of multiple training repetitions at various levels is a clinically undesirable requirement.

Figure 5 shows the mean normalized contraction level with respect to the 100% class-specific MVC. Note that, on average, the light, medium, and hard levels roughly correspond to 20%, 40%, and 70% MVC. The wrist supination class light and medium levels tended to be higher than those of the other classes.

B. Session 2: Tracking test analysis

Figure 6 shows the classification error for all combinations of training method and gain level. Note, again, that the gain levels depicted along the horizontal axis correspond to the gain necessary to map a class specific mean to that percentage of the dynamic range.

Figure 7 shows the corresponding R^2 tracking score. A multi-way ANOVA (with post-hoc multiple comparison test) indicated a significant interaction ($p < 0.001$) between training method and gain level. As a result, an f-test was performed comparing the variability in the R^2 tracking score of the two training methods due to changes in gain level. The results showed that training with ramp data produced a control scheme that was significantly more tolerant to variations in gain level.

The ANOVA analysis showed that training with the dynamic ramp data significantly improved ($p < 0.001$) both classification error ($14.84 \pm 0.60\%$ and $11.16 \pm 0.54\%$ for medium and ramp training, respectively) and R^2 tracking score (0.1458 ± 0.0368 and 0.3279 ± 0.0276 for medium and ramp training, respectively) during the tracking task. It also showed that the selection of gain level had a significant effect ($p < 0.001$) on both classification error (Figure 8) and R^2 tracking score (Figure 9). In both cases, selecting a gain level that mapped the class-specific mean proportional control value to 60% of the full dynamic range provided the best performance. Again, note that in Figures 8-11, non-overlapping intervals indicate a significant difference between comparisons.

Figures 10 and 11 show the classification error and R^2 tracking score, respectively, broken up by class. Note that the wrist extension class was significantly worse than the other classes in both cases. Wrist flexion was significantly better than the other classes with respect to classification accuracy, but not so for R^2 tracking.

DISCUSSION

This work was divided into two sections. The first section, *Session 1*, looked at classification error when training with one contraction level but testing with others. This is analogous to common clinical pattern recognition studies where users are instructed to elicit a repeatable *medium level* contraction during training then asked to use proportional control during usability testing. As seen in Figure 4, these *medium level* contractions indeed offer the best performance out of the static level choices. It is evident however, that performance quickly degrades as static training levels deviate from the 40-50% range. The *ramp* training scheme significantly outperformed all level based schemes. This is likely due to the presence of exemplars from many contraction levels in the resultant training data. Additionally, the dynamic nature of the ramp contraction bodes well for suitability during equally dynamic proportional control tasks.

The class-specific user elicited contraction levels were shown in Figure 5. When prompted to elicit *hard* contractions without feedback, the average corresponding normalized levels reached between 60 and 70%. This implies that anything higher than a 60% is simply unsustainable for most users. Similarly, the user elicited *light* contraction, described to users as 'as light as possible while still performing the class contraction', was limited to approximately 20%. These results yield a suggested usable range of 20-60% of class specific MVC. Users often stated difficulty in achieving the higher level targets when using the wrist supination class. This is thought to be due to a reduced dynamic range in the forearm signals corresponding to wrist supination. The theory is supported by the shift in user elicited contraction levels compared to the other classes (Figure 5). This could be alleviated by including electrodes over the biceps (the prime movers for supination), but it is not a clinically desirable arrangement.

The second part of the study, Session 2, used lessons learned during Session 1 to perform a real-time amplitude tracking test with feedback. The tracking cursor was hidden when the classifier concluded that the user was performing an erroneous class contraction. This behavior was chosen because a prosthesis user would be unable to track a given degree of freedom while unintentionally activating another. Consequently, users were asked to focus on reestablishing the correct classification before concentrating on tracking. This predictably created a strong relationship between classification error and tracking score.

As learned in Session 1, using a ramp contraction during training greatly improves the classifier's performance when testing with various contraction levels. This theory held true during the proportional tracking test, yielding a significant improvement over the standard medium level contraction. Furthermore, it was shown to provide superior resilience to sub-optimal gain selection.

Gain selection was also shown to have a significant effect on classification accuracy and tracking ability. This is an important finding of this work as clinical practice currently consists of manually setting gains based on empirical observation. These results indicate that, on top of simplifying the clinical configuration process, auto-gain selection could ensure optimal performance of a pattern recognition based myoelectric control system.

There is also a tradeoff between gain level and user effort level. Users indicated a preference for higher gains due to ease of contraction, but complained of an associated "jumpiness" or lack of controllability. Conversely, users expressed strong aversion to lower gain levels because of an inability to produce higher control signals. When using lower gains, many users resorted to eliciting pulsatile/burst contractions to approach higher targets and some gave up altogether. Consequently, the level of user effort must be taken into consideration when choosing gain levels. Fortunately, the algorithmically determined optimal gain levels correspond with those empirically preferred by the users.

It is instructive to note that, in this work, as in previous work examining the effect of limb position on classification error,¹⁶⁻¹⁷ the robustness of myoelectric control seems to be related to the proper population of feature space. Training data collected using "repeatable medium level" contractions with the limb in a rested position (as is often the norm in myoelectric controls research) can produce good *offline* classification accuracies. The resultant feature space is, however, sparse and the true class boundaries are under-defined. Under more challenging usage scenarios, these boundaries are tested by dynamically varying contractions and class transitions resulting in undefined classifier behavior. It is the opinion of the authors that proper population of feature space and definition of class boundaries will play an integral role in the deployment of clinically viable pattern recognition based myoelectric control systems.

Finally, it should be noted that this study was conducted using normally limbed subjects. Because this study provided an introductory look at the effects of force variation on classification, the data collection protocol was onerous, at times requiring intense contraction of the muscles. Completion of the protocol, especially by amputee patients, was demanding; something we endeavor to shelter our patients from. In previous work by Scheme et al.,²⁵ it was shown that the relative trends when comparing myoelectric control schemes were consistent between normal and amputee populations. While the end goal of any prosthetics research remains to develop and test algorithms for the end-user, we believe that using normally limbed subjects in the early investigation and validation of control algorithms is justified.

FUTURE WORK

This work has shown that the use of proportional control has a significant effect on classifier performance. Consequently, the authors are currently performing an ongoing study looking at algorithmic approaches to alleviating proportional control induced classification errors. Alternate methods of deriving the proportional control signal are also being investigated.

This work is part of a larger investigation aimed at understanding and mitigating the factors that limit the clinical robustness of myoelectric control.

Acknowledgments

Funding Sources: This work was supported in part by NSERC Discovery Grant 217354-10, NIH Grant 5R01HD058000-03 and the Atlantic Innovation Fund

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Figure 1.
Seven classes of contractions used throughout this study.

Figure 2.
Real-time tracking test.

Figure 3.

Example of effect of contraction strength on features. In this figure, features from a simple 3 class problem (no motion: NM, wrist flexion: WF, and wrist extension: WE) were projected using uncorrelated linear discriminant analysis (ULDA) and the two most discriminatory dimensions are shown.

Figure 4.
Classification error (%) when testing with all levels.

Figure 5.

Average normalized level of user elicited "light," "medium," and "hard" contractions for classes wrist flexion (WF), extension (WE), pronation (WP), supination (WS), hand close (HC) and hand open (HO).

Figure 6.
Classification error for varying gain levels and training method.

Figure 7. R^2 tracking score for varying gain levels and training method (note that contrary to classification error, higher R^2 scores indicate better tracking performance).

Figure 8.
Classification error during tracking test for different gain levels.

Figure 9.
R² error during tracking test for different gain levels.

Figure 10.
Classification error during tracking task, displayed by class.

Figure 11.
R² tracking score during tracking task, by class.

Table 1

Intra-level (boxes) and inter-level classification error

Test Level (% Of Class Specific MVC)												
	Light	Medium	Hard	20	30	40	50	60	70	80	Ramp	
Training Level (% Of Class Specific MVC)	Light	16.6	27.9	37.3	37.6	32.7	31.3	36.5	35.3	40.9	41.1	35.2
	Medium	43.8	12.9	13.2	56.8	39.8	22.2	20.2	17.8	19.5	21.0	25.9
	Hard	57.8	22.7	10.5	68.6	52.2	33.8	23.1	14.7	11.6	10.5	29.7
	20	34.2	40.3	50.8	19.6	20.9	31.6	40.3	44.5	49.3	50.2	34.5
	30	38.7	25.9	38.1	33.7	12.8	11.5	20.4	29.8	33.7	35.0	25.9
	40	47.3	19.9	24.0	58.2	23.1	5.5	5.8	12.9	17.5	23.4	19.9
	50	56.8	22.0	14.9	69.7	43.2	11.4	4.6	5.2	6.9	11.5	22.3
	60	60.1	27.3	12.4	72.8	60.5	29.6	8.9	3.3	3.1	3.4	25.4
	70	64.5	37.8	13.3	76.0	69.2	46.3	17.4	3.8	2.7	1.9	30.2
	80	64.5	43.3	18.6	77.3	72.1	57.1	32.5	9.6	5.5	2.1	36.1
Ramp	34.1	19.7	19.9	34.7	21.4	12.7	12.1	10.9	12.2	12.1	11.9	