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A Comparison of Proportional Control Methods for Pattern Recognition Control

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Abstract— **Few studies have focused on proportional control with multi-channel electromyographic (EMG) pattern recognition systems. In a simple proportional control algorithm, movement speed is often calculated by averaging the mean absolute values of all EMG channels. The aim of our study was to compare the performance of two types of pattern recognition control (simple proportional and binary on/off) to direct proportional control. Six EMG channels were collected from non-targeted forearm muscles of four healthy subjects. Subjects were prompted to perform eight medium force isometric repetitions of the following contractions: wrist flexion/extension, wrist pronation/supination, hand open/close, and no movement (rest). Control performances were measured during a one-dimensional position-tracking task using a custom-made graphical user interface. The results show that a simple proportional control algorithm for the pattern recognition system outperformed binary on/off control and was comparable to the performance achieved with direct proportional control.**

I. Introduction

The concept of myoelectric control originated in the late 1940s and since then, various implementation strategies have been devised [1]. Direct proportional control and binary on/off control are two methods often used in clinical setups. In a typical direct proportional control setup, electrodes are placed on an agonist/antagonist muscle pair and the amplitude envelopes of the electromyographic (EMG) signals are used to determine when and at what speed the device operates. In binary on/off control, the amplitude envelopes of the EMG signals are compared to thresholds and when the thresholds are exceeded the device operates at one speed. The thresholds and speed of activation are configured by a clinician during the fitting process. These types of control have been investigated extensively [1] and received widespread clinical implementation.

EMG-based pattern recognition control systems can discriminate between many degrees of freedom (DOF) and have shown promising results in laboratory experiments [2-4] but have yet to be clinically implemented. Few studies have focused on using proportional control with multi-channel EMG pattern recognition systems [5], and the lack of a robust proportional control algorithm is a barrier to clinical implementation. A simple weighted average of the mean absolute value (MAV) of all measured EMG channels has been proposed as a pattern recognition proportional control algorithm; however, its performance has not yet been quantified.

II. Methodology

Four non-amputee subjects participated in this study. The Northwestern University Institutional Review Board approved the experimental procedure and each subject provided informed consent prior to participating in the experiment.

Six bipolar surface EMG channels were positioned at equidistant locations around the circumference of the forearm approximately one-third of the distance from the elbow to the wrist and proximal to the elbow. Subjects were prompted to perform eight medium force isometric repetitions—with arm and hand both constrained in a custom built brace— of the following seven contractions: wrist flexion/extension (WFE), wrist pronation/supination (WPS), hand open/close (HOC), and no movement (rest). Each contraction was held for 3 s and the data were divided such that 12 s of each class were used for training, and 12 s of each class were used to compute offline classification error. EMG signals were amplified using a Deslsys Bagnoli 16 EMG system and sampled at 1 kHz using a 16-bit National Instruments DAQ.

A feature set composed of four time domain statistics was used to process the data. The feature set (number of zero crossings, waveform length, number of slope sign changes, and mean absolute value for a given data window) has been used previously in real time EMG control schemes [2, 6]. The data were segmented into frames of 150 ms from which these features were computed. Overlapping frames were used and frames were incremented at 40 ms. The features from each channel were then concatenated into an aggregate feature vector and used as inputs to a linear discriminant analysis (LDA) classifier; this feature set classifier has been shown to yield high classification accuracies [2, 6].

A custom-made graphical user interface (GUI) to perform a tracking task, modeled after Corbett et al. [7], was implemented in MATLAB (Mathworks Inc., Natick, MA). In this tracking task, subjects had real-time control of a red cursor and were instructed to trace a target waveform that scrolled across the screen (Figure 1). The cursor represented the joint position and not joint velocity. The maximum

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position that the cursor could move in each frame was set to 4 degrees, which corresponded to a movement speed of 100 degrees per second. This value was chosen based on pilot experiments.

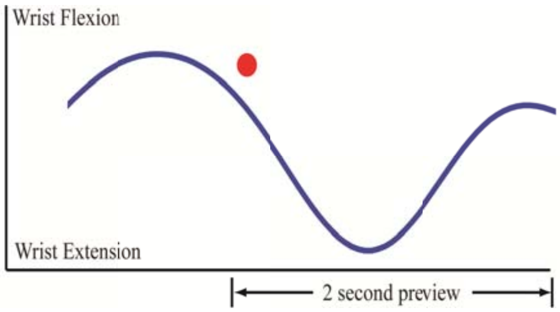

Figure 1. Example of GUI implemented through MATLAB that displays the tracking test modeled after Corbett et al [7].

The classifier was trained to recognize all degrees of freedom but the tracking experiment was performed on each DOF separately; if the classifier output decisions corresponded to other DOFs the red cursor did not move. Subjects aimed to trace a 0.8 Hz band-limited Gaussian white noise waveform. Subjects were allowed three practice sessions—one for each DOF—before testing to familiarize themselves with the tracking task prior to evaluation. Each DOF was tested twice for a total of six trials for each type of control. Trials were 35 seconds long but only the last 10 seconds of each trial was analyzed because it took time for subjects to achieve steady-state tracking performance.

Three types of control were tested, including direct proportional control, pattern recognition with binary on/off control, and pattern recognition with a simple proportional control algorithm.

Direct Proportional Control: Only the wrist flexion/extension DOF was tested using direct proportional control. In this setup, two of the six EMG channels were used; one directly over the forearm flexor muscle group and one directly over the extensor muscle group. Movement speed was calculated as the MAV of the higher of the two EMG channels.

Gains and thresholds were adjusted manually such that subjects' average contraction resulted in a nominal speed. In this work, the nominal speed was chosen to be 50% of the maximum speed or 50 degrees per second. By performing a lighter or harder muscle contraction, subjects could move at slower and faster speeds.

On/off Pattern Recognition Control: For this setup, the cursor was either at rest, or moved at a constant speed. During pilot work, we noted that subjects preferred a slower maximum movement speed than what was used for direct proportional control. Consequently, the maximum cursor speed for on/off control was reduced to 50 degrees per second. The subjects felt that this was a comfortable speed at which to move the cursor.

Simple Proportional Pattern Recognition Control: During simple proportional control, movement speed was a function of the MAV of the EMG channels. Class-specific proportional output was calculated according to the following formula:

$$O_j = G_j\left(\frac{1}{N}\sum_{i=1}^{N} MAV_i - T_j\right) \tag{1}$$

Where O_j is the output speed of class j; G_j is the applied class gain; T_j is the applied class threshold, MAV_i is the mean absolute value of channel i for the current, real-time computation window, and N is the total number of channels.

Similar to direct proportional control, gains and thresholds were manually configured such that subjects' average contraction resulted in 50% of the maximum movement speed. By performing a lighter or harder muscle contraction, subjects could move at slower and faster speeds.

The primary metric used to evaluate tracking task performance was root mean square (RMS) error. The RMS error is calculated using the following equation:

$$RMS\,Error = \sqrt{\frac{\sum_{k=1}^{T} \Delta y_k^{\;2}}{N}} \tag{2}$$

Where Δy is difference between the subject's cursor position and the target waveform position at time k, and T is the total number of frames that were analyzed. The RMS error was normalized by dividing the RMS error by the RMS value of the target waveform. A linear mixed effects model was created to complete a statistical analysis. The RMS error was the response variable; the trial, proportional control algorithm type, and DOF were set as fixed effects; and the subject was set as a random effect.

The offline classification error of the pattern recognition system was computed. This is defined as the proportion of correct decisions that the classifier made when the 12 seconds of labeled test data were evaluated. The real-time classification accuracy—termed the real-time efficiency—was also computed by analyzing the tracking files. The subjects were attempting to control a single DOF during each tracking trial. The real-time efficiency was the proportion of time the classifier made a decision corresponding to the DOF being tracked.

III. RESULTS

Average pattern recognition classification error was 1.3% for all subjects. Table I displays a confusion matrix of the offline classification errors, grouped by DOF. Figure 2 displays example tracking performance of the wrist flexion/extension DOF for one subject across all three control schemes.

The linear mixed effects model showed significant differences ($p<0.05$) between direct control, simple proportional pattern recognition control, and on/off pattern recognition control. Direct control performed best, followed by simple proportional control and on/off control (Figure 3). The linear mixed effects model also showed that the DOF was a significant factor ($p<0.05$). Subjects did not track wrist supination/pronation as well as wrist flexion/extension or hand open/close.

Table I.
Confusion matrix showing the distribution of offline classification errors. The same LDA classifier was used in both the on/off and simple pattern recognition tracking experiments. The values are averaged over the four subjects. A perfectly accurate system would have 100s on the diagonal and 0s elsewhere.

Target DOF \ Predicted DOF	WFE	WPS	HOC
WFE	96	2.5	1.5
WPS	0	100	0
HOC	0	0	100

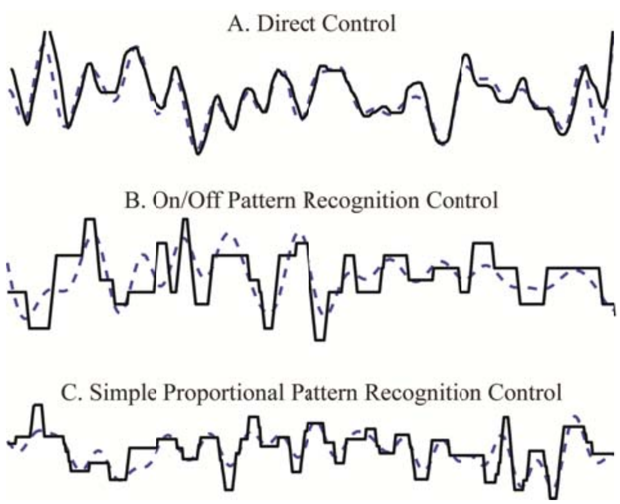

Figure 2. Example trials of the wrist flexion/extension DOF for: A) direct proportional control condition, B) on/off pattern recognition control condition, and C) simple proportional pattern recognition control condition. The target waveform is the dashed line and the subject's tracking performance is the solid line.

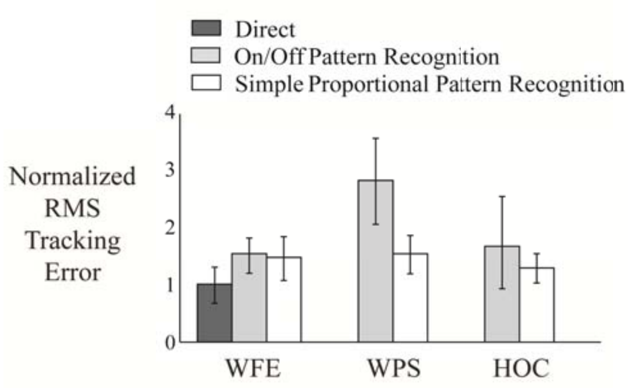

Figure 3. Normalized RMS tracking error for each DOF and control method. Error bars denote one standard error about the mean

Tables II and III show confusion matrices of the real-time efficiency for the simple pattern recognition proportional control and on/off pattern recognition proportional control.

IV. Discussion

Direct proportional control has been used clinically for many years. It is straightforward to map amplitude of single EMG channel to speed along a single degree of freedom. In this experiment, only two direct proportional control sites were localized. Consequently, the direct control tracking experiment was completed for the wrist flexion/extension DOF because it was a physiologically appropriate DOF which generated independent EMG signals at the direct proportional control sites. Pattern recognition systems usually use multiple EMG channels to determine which DOF is being activated. Consequently, it is not appropriate to map the amplitude of a single channel to the speed of actuation, but proportional control is still a desirable characteristic.

Table II.
Confusion matrix showing the real-time efficiency of the simple pattern recognition proportional control scheme. The values are averaged over the four subjects. A perfectly efficient system would have 100s on the diagonal and 0s elsewhere.

Tracking DOF \ Predicted DOF	WFE	WPS	HOC
WFE	47	34	19
WPS	0	93	7
HOC	2	28	70

Table III.
Confusion matrix showing the real-time efficiency of the on/off pattern recognition control scheme. The values are averaged over the four subjects. A perfectly efficient system would have 100s on the diagonal and 0s elsewhere.

Tracking DOF \ Predicted DOF	WFE	WPS	HOC
WFE	40	40	20
WPS	0	93	7
HOC	0	33	67

The results demonstrate that pattern recognition-based proportional control can be achieved using a simple weighted average of the MAV of all channels. Such a system performs better than the on/off control method but does not perform as well as direct proportional control. Although the simple proportional control algorithm used in the current study resulted in a similar level of performance as direct proportional control for wrist flexion/extension, a more advanced algorithm may provide additional benefits for other DOFs. Manual adjustment of gains was a subjective process and relied heavily on the skill of the experimenter. With pattern recognition, however, EMG data for each movement is already collected and stored. An enhanced proportional control algorithm utilizing this data may be able to automatically calculate these individual class gains thereby reducing the clinical configuration time.

There were large differences between the offline classification accuracies and the real-time efficiencies. The pattern recognition experiments were performed using a LDA classifier. This classifier has been shown to be computationally efficient and to produce the same classification accuracies as more complex, nonlinear classifiers [8] during offline experiments. We believe that the muscle activation patterns crossed decision boundaries in feature space when users modulated the force of their contractions. This behavior has been observed in a previous pattern recognition study investigating the relationship between accuracy and muscle contraction force [8]. The current classifier appeared to be very sensitive to the wrist pronation/supination DOF; there were many wrist pronation/supination misclassifications when the user attempted to control wrist flexion/extension and hand open/close. This highlights a major challenge when implementing proportional control for pattern recognition systems; the system must remain accurate when users attempt to modulate the actuation speed of the prosthesis. In our test, the cursor remained stationary if an erroneous decision was made, as shown by flat regions in Figure 2B and 2C.

The pattern recognition training and testing data were collected when subjects made repeatable ‘medium’ force isometric contractions to the best of their ability. The precise force of the contraction was not measured, nor was any feedback provided to the subjects. In future work, we will instruct subjects to modulate the force of the contractions during training data collection and determine the classification accuracy and real-time efficiency relationship. We hypothesize that data collected during modulated force contractions will improve tracking performance and yield a classifier with higher real-time efficiency.

This experiment had limitations that should be taken into account. The subjectivity of adjusting control gains may have affected user performance during the tracking task. To reduce this effect, one experimenter set up the control for all subjects across all conditions. In addition, on/off pattern recognition control used slower speeds (i.e. another type of gain) compared to the two other control schemes. This slower maximum speed may have resulted in lower RMS error for on/off control. Subject performance may have also been affected by learning. At the end of the experiment, subjects noted that they could perform the tracking task better, regardless of the control scheme. Increasing practice durations and/or varying tracking frequencies may have resulted in RMS error values more similar to previous studies [7]. The pattern recognition training data were collected from medium, isometric force contractions. We expect that data collected from a variety of different force levels would improve the real-time efficiency of the classifier [8]. We believe that this would also improve the tracking performance that the users could achieve.

Finally, the results are for a limited sample of non-amputee subjects with normal musculature. Further testing is necessary to see if pattern recognition proportional control can also be achieved by amputees.

V. Conclusion

This demonstration of proportional control reduces one more barrier to the clinical implementation of multi-channel EMG pattern recognition. Proportional control is necessary to allow users to perform fine or gross movements with ease. The simple control algorithm tested in this study allows for these types of movements, but did not perform as well as direct proportional control. An enhanced algorithm that reduces the clinical configuration burden and further improves tracking ability is desirable.

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