Optimizing Pattern-Recognition-Based Control for Partial-Hand Prosthesis Application

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***Abstract* — Partial-hand amputees often retain good residual wrist motion, which is essential for functional activities involving use of the hand. Thus, a crucial design criterion for a myoelectric, partial-hand prosthesis control scheme is that it allows the user to retain residual wrist motion. Pattern Recognition (PR) of electromyographic (EMG) signals is a well-studied method of controlling myoelectric prostheses. However, wrist motion can obscure these signals and interfere with PR accuracy. We studied the effects of (1) window length and number of hand-grasps, (2) static and dynamic wrist motion, and (3) EMG muscle source on the ability of a PR-based control scheme to classify functional hand-grasp patterns. Our results show that training PR classifiers with both extrinsic and intrinsic muscle EMG yields a lower error rate than training with either group by itself (p<0.01); and that including static and dynamic wrist data in the training set results in lower error rates than including no wrist information, or only static or dynamic wrist information. Finally, our results show that both an increase in window length and a decrease in the number of grasps available to the classifier significantly decrease classification error (p<0.01), though there is no interaction between the two (p=0.33). These results remained consistent whether the classifier was selecting or maintain a hand-grasp.**

I. Introduction

Partial-hand amputation is the most common form of upper-limb amputation affecting an estimated 455,000 individuals in the United States as of 2005 [1]. Myoelectric prostheses that use surface electromyographic (EMG) signals to control joint movements [2] have only recently become available to partial-hand amputees with the introduction of small, lightweight partial-hand prostheses such as motorized fingers. These devices potentially provide the user with functional hand-grasps not previously available, but their potential benefits are limited by their control method [3]. To date, these devices have been controlled using touch-sensitive resistors or conventional myoelectric control strategies that commonly use the amplitude of EMG signals to control the speed of the prosthesis. The source of EMG signals can either be the intrinsic hand muscles, located in the hand, or the extrinsic hand muscles, located in the forearm. Though conventional control using intrinsic hand muscle EMG allows retention of residual wrist motion, it limits the user to the control of one prosthetic function unless an unintuitive switching mechanism is employed. Alternatively, extrinsic hand muscle EMG can be used, but this compromises normal wrist movement and thus limits function [4].

Pattern Recognition (PR) of extrinsic muscle EMG is a method that provides the user with more intuitive control of a greater number of prosthetic functions [5-7]. PR classifiers can discriminate between hand-grasps by comparing EMG patterns acquired while performing a grasp to previously-collected training data. However, the EMG signals generated by the wrist muscles can obscure extrinsic hand muscle EMG, thus degrading PR performance. It has been shown that using intrinsic muscle EMG, and including examples of grasp pattern EMG while the wrist moves through various static and dynamic wrist positions, in the PR training algorithm mitigates, though does not negate, this effect [8].

Several techniques can also be employed to improve PR performance. First, PR performance improves when increasing the quantity of data analyzed via a longer EMG window length, which generates a more robust training set [9]. Second, reducing the number of classes available to the classifier can improve performance. As the number of hand-grasps available to the classifier decreases, the rate of incorrect classification, and therefore the error rate, generally decreases. These two techniques have been used to improve the robustness of hand-grasp selection and control for high-level Targeted Muscle Reinnervation (TMR) amputees [10].

The purpose of this study is to determine the PR factors that will maximize classifier performance for a partial-hand prosthesis application. To achieve this goal, the effects of the following three factors on PR performance were investigated: (1) training the classifier with the wrist in multiple static and dynamic positions; (2) training the classifier with the extrinsic hand muscles, intrinsic hand muscles, or a combination of both muscle sets; and (3) training the classifier with varying numbers of hand-grasps and multiple window lengths.

II. Methods

A. Experimental Protocol

Nine non-amputee subjects were recruited for this study, which was approved by the Northwestern University

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Institutional Review Board. Eight bipolar, self-adhesive, surface Ag/AgCl EMG electrodes were evenly placed longitudinally around the circumference of each subject's non-dominant forearm: six around the proximal forearm, one on the anterior side of the distal forearm, and one on the posterior side of the distal forearm. Four bipolar electrodes were placed on the hand: one on the thenar eminence, one on the hypothenar eminence, one on the dorsal hand between the first and second metacarpals, and one on the dorsal hand between the third and fourth metacarpals. Each bipolar electrode had an inter-electrode distance of 4cm [11]. The reference electrode was placed over the lateral epicondyle of the humerus [see Fig. 1]. Both the forearm and hand were lightly wrapped with an elastic, cohesive bandage.

Subjects performed six different functional hand-grasps. These grasps, in order of most to least often used for activities of daily living (ADLs) [12], included chuck grip, fine pinch, key grip, power grip, hook grip (as one would hold a briefcase handle), and tool grip (similar to squeezing the trigger of a power drill). Subject also performed a Hand Open (HO) posture and a No Movement (NM) posture.

Data were collected under ten conditions and analyzed offline. For the first condition, subjects held a grasp for 4 seconds in a neutral wrist position; this was done 4 times for each grasp, including HO and NM. This procedure was repeated with a comfortable level of wrist flexion, extension, radial deviation, ulnar deviation, pronation, and supination; these seven conditions made up the static wrist data set. Subjects then performed each grasp 4 times while moving the wrist from a comfortable flexion position to a comfortable extension position, and back to flexion; and 4 times while moving the wrist from extension to flexion, and back to extension; each over the span of 4 seconds, or 2 seconds of movement in each direction. This procedure was repeated for radial and ulnar deviation, and pronation and supination; these three conditions made up the dynamic wrist data set. Data were then separated into training and testing sets for the PR algorithm, and analyzed using two-fold cross-validation.

B. *Signal Processing*

EMG signals were sampled at 1000 Hz, with a band-pass filter between 30-350Hz, using a TI ADS1298 chip. Signal acquisition was guided using custom-built computer software. Pattern recognition was performed via linear discriminant analysis (LDA) classification with 4 time domain (mean, zero crossings, turns, waveform length) and 6 auto-regressive features [13]. LDA was selected as the pattern recognition algorithm due to its relatively simple calculations and computational efficiency [14]. Additionally, preliminary experiments showed that the LDA classifier performed comparable or superior to both the Gaussian Mixture Model (GMM) and Support Vector Machine (SVM) classifiers. Classification error, defined as the percentage of incorrect classifications, was used to evaluate classifier performance.

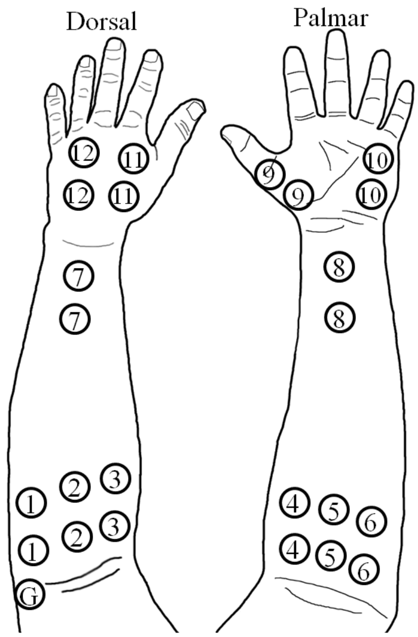

Figure 1. Electrode placement during experiment. Electrodes 1-8 record extrinsic muscle EMG, while electrodes 9-12 record intrinsic muscle EMG. The ground (G) is placed on the lateral epicondyle of the humerus.

C. *Data Analysis*

Hand-grasp tasks may be separated into two categories: grasp selection and grasp maintenance. During grasp selection, the classifier selects the correct grasp from the available classes consisting of *N* grasps, HO, and NM, or a total of *N+2* classes. After a grasp is selected, the grasp maintenance mode is activated; in this mode, all available grasps are mapped to a new class labeled Hand Close (HC), resulting in only three classes and fewer instances of misclassification. In addition, NM predictions when the desired class is HC are also labeled as correct.

For this study, grasp selection was only performed with a static wrist, while grasp maintenance could be performed with either a static or dynamic wrist. From an application perspective, this equates to prepositioning the wrist prior to making a hand-grasp selection. After selection, the user is free to move his or her wrist while maintaining the selected grasp. Thus, the PR classifier for grasp selection was tested with static wrist data only, and the PR classifier for grasp maintenance was tested with both static and dynamic wrist data.

1) *Training Method and Electrode Placement*

Four different classifier training methods were evaluated These training methods were (1) training with the wrist only in the neutral position, (2) training in the seven static wrist positions, (3) training while moving the wrist along each of its three degrees of freedom, and (4) training with all static + dynamic wrist data included in the classifier. This analysis was performed with 6 available grasps and a 250ms EMG window with a 25ms frame increment, using only extrinsic muscle EMG signals.

Electrode placement conditions were separated into three groups consisting of (1) extrinsic muscles, (2) intrinsic muscles, and (3) extrinsic + intrinsic muscles; each was performed with the above-mentioned static + dynamic training scheme, with 6 available grasps, and with a 250ms window and 25ms frame increment. Statistical analyses were calculated with a 2-way analysis of variance (ANOVA), and post-hoc comparisons were made using a Bonferroni correction factor to determine significance.

2) Window Length and Available Grasps

For tests run with the static + dynamic classifier and only the 8 extrinsic EMG channels; PR performance was evaluated for window lengths of 100, 200, 300, 400, and 500ms; and for 2, 4, and 6 available grasps, where the grasps analyzed were the *N* most commonly used hand-grasps in ADLs. Statistical analyses were calculated with a 2-way ANOVA, and post-hoc comparisons were made using a Bonferroni correction factor.

III. Results

A. Training Method and Electrode Placement

For grasp selection, including wrist motion in the training data set significantly improved PR performance [see Fig 2(a)]. The static training method yielded the lowest error (17.29%), though this was not significantly different from the static + dynamic training method (20.89%, p=0.40). For grasp maintenance, including wrist motion also improved performance [see Fig 2(b)]. However, there was no significant difference between static, dynamic, or static + dynamic training methods (p>0.61).

During grasp selection, although only four intrinsic channels were analyzed, the error rate for intrinsic channels (19.20%) was similar to extrinsic channels (20.89%); both had significantly higher error rates than extrinsic + intrinsic channels (5.89%, p<0.01) [see Fig. 3(a)]. However, for grasp maintenance, the differences in error rate between extrinsic (6.29%), intrinsic (4.33%), and extrinsic + intrinsic (1.50%) channels were significant (p<0.01) [see Fig. 3(b)]. There was also significant interaction between training method and electrode placement for both grasp selection and maintenance (p<0.01), which demonstrates the reduced sensitivity of intrinsic channels to wrist position compared to extrinsic channels.

B. Window Length and Available Grasps

As found in previous studies [9], increasing the classification window length reduced error (p<0.01). In addition, providing fewer available grasps also reduced error (p<0.01) [see Fig. 4]. There was no interaction between the two factors (p=0.33). During grasp selection, all windows were significantly different from others (p<0.01) with the exceptions of 300ms (14.40%) and 400ms (12.79%) windows (p=0.19), and 400ms and 500ms (11.63%) windows (p=0.92) [see Fig. 4(a)]. During grasp maintenance, all windows were significantly different (p<0.05), though the maximum difference was less than 4% error [see Fig. 4(b)].

IV. Discussion

Because training a classifier with the wrist in the neutral position does not take static or dynamic motions into account, it is understandable that the errors for this classifier

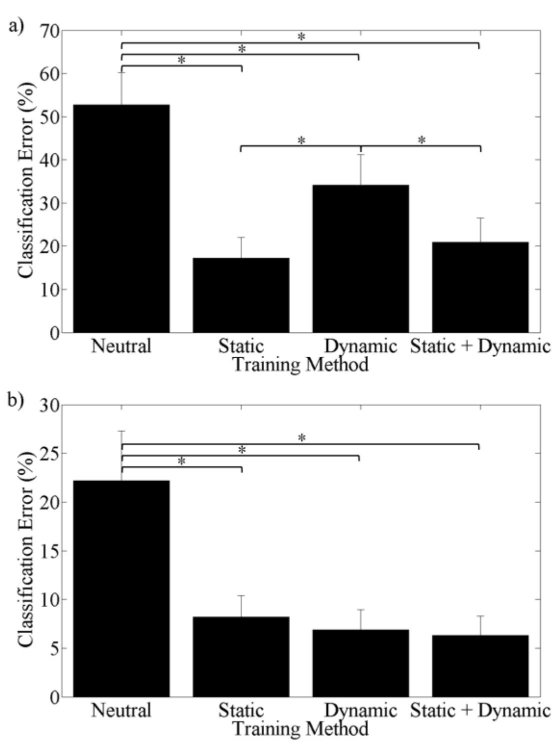

Figure 2. Training Method Classification Error. Asterisk (*) represents p<0.01. (a) Classification error during grasp selection (b) Classification error during grasp maintenance

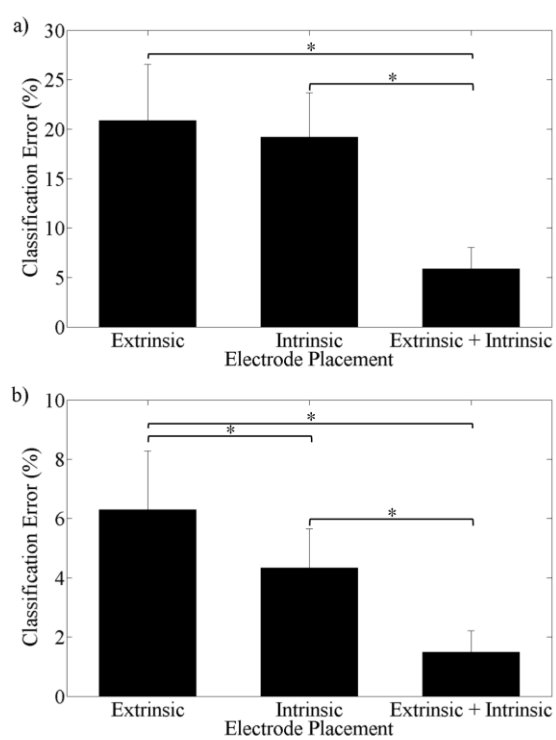

Figure 3. Electrode Placement Classification Error. Asterisk (*) represents p<0.01. (a) Classification error during grasp selection (b) Classification error during grasp maintenance

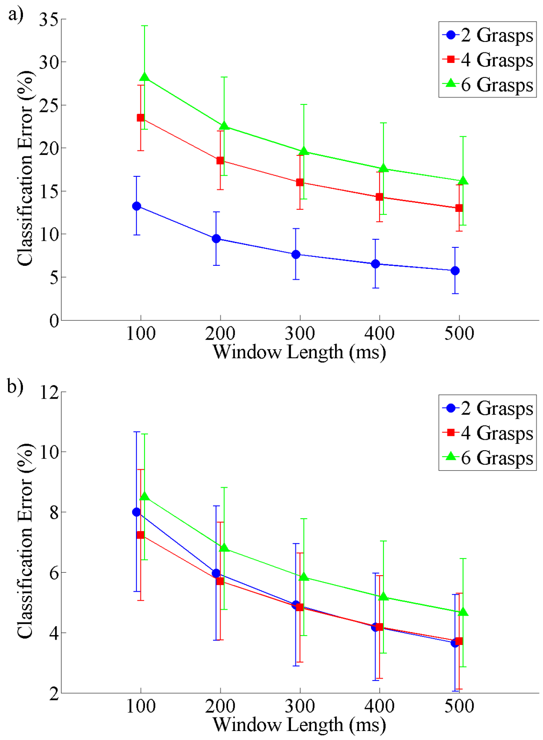

Figure 4. Interaction of Window Length and Available Grasps (a) Interaction during grasp selection (b) Interaction during grasp maintenance

are much higher than classifiers containing training data during wrist movements. Though training with only static data yields lower error than training with static and dynamic data when selecting a grasp, it is not robust to dynamic wrist motion. If only one training method is used for partial-hand prosthesis applications, the use of a training set with both static and dynamic data is recommended. Intrinsic EMG yielded lower error rates than did extrinsic EMG in both grasp selection and grasp maintenance tests, though the difference during grasp selection was not statistically significant. Including both extrinsic and intrinsic EMG in a classifier significantly reduces the error compared to either group by itself, supporting the findings of previous studies [8]. If a prosthesis design allows for electrodes to be placed on the hand, the use of intrinsic muscle EMG is recommended.

Longer window lengths provide lower error than shorter window lengths, but at the cost of increased response delay [9]. Consequently, one must balance the speed and accuracy of the system to provide optimal performance. These results show that window length has a minimal effect on accuracy while maintaining a grasp; therefore, though longer windows are important during grasp selection, shorter windows can be used during grasp maintenance while preserving accuracy.

V. Conclusion

For partial-hand prosthesis application, including wrist motion in a PR classifier, and selecting appropriate window lengths, is important to ensure a robust system. This allows the user to operate the prosthesis and still maintain the ability to freely position the wrist in space, thus significantly improving function. Also, though acquiring EMG from intrinsic muscles can be difficult, these data can compliment extrinsic muscle EMG for significantly improved prosthetic performance.

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