The Effect of Wrist Position and Hand-Grasp Pattern on Virtual Prosthesis Task Performance

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***Abstract*— Partial-hand amputees are often able to use their wrist when performing daily activities, but this wrist movement can interfere with electromyogram (EMG) pattern recognition of functional hand-grasps while controlling myoelectric prostheses. These grasp patterns also commonly require activation of similar muscle sets, resulting in poor discrimination and more frequent misclassification. In our recent work, we developed a classifier training paradigm and control system that improves real-time control of a virtual prosthesis capable of selecting between 4 grasps in multiple wrist positions. However, it is unclear if there were adverse effects associated with operating the virtual prosthesis in certain wrist positions or with attempting to select specific grasps. The primary purpose of this study is to determine whether the required wrist position or grasp affected task timeout rates, and to determine the number of grasp selection attempts for both a baseline pattern recognition controller and our proposed controller. We show that the specific wrist position of a given task does not significantly affect performance for either the baseline controller (*p*>0.575) or the proposed controller (*p*>0.459). However, while the grasp required for a task significantly affects a user's ability to complete the task when using the baseline controller (*p*<0.05), this is not the case with the proposed controllers (*p*>0.429). Thus, subjects using the proposed controllers were more easily able to complete tasks involving grasps difficult to select with the baseline controller.**

I. INTRODUCTION

By the year 2020, an estimated 650,000 individuals in the United States will be living with a partial-hand amputation [1], and currently 91% of the 18,500 upper extremity amputations each year occur distal to the wrist [2]. Partial-hand amputation has a significant impact on an individual's perception of self [3] and their ability to work [4], [5] and perform daily tasks [6], [7].

Recently, externally-powered prosthetic hands, or myoelectric prostheses, have been made available to partial-hand amputees, such as the iLimb [8]. These devices are controlled by reading surface electromyographic (EMG) signals from electrodes embedded in the socket. Although prosthetic fingers and hands can restore functional hand-grasps to partial-hand amputees, they are commonly controlled in the same manner as transradial prostheses, i.e. contracting antagonist muscle pairs to control a single grasp. If the user wants to select a different grasp, they must co-contract the muscle pairs in a specific pattern to initiate a mode switch.

One control method prevalent in prosthesis research uses pattern recognition algorithms with recorded EMG signals to determine the movement desired by the user [9]–[11]. In prosthesis applications, these can be used to predict a user's intended arm movement [12], [13] or predict the movement of individual fingers [14]–[16] However, much of this research focuses on control of transradial or transhumeral prostheses, and as such does not address the unique challenges of real-time partial-hand prosthesis control. First, partial-hand amputees often still have an intact wrist, which is integral to performing many daily tasks. Unfortunately, moving the wrist has been shown to interfere with pattern recognition of grasps [17], [18]. Second, physical constraints on commercially-available componentry require the prosthesis to move through a predefined trajectory to switch operational grasps. Often, the prosthesis requires a hand to be positioned in a neutral, or fully-open, position before switching to a different grasp. Using this principle, we have created a unique pattern recognition control paradigm where a grasp can only be selected if the prosthetic hand is fully open, otherwise all grasp predictions are simply mapped to further close the hand in the locked-in grasp [see Fig. 1]. If the controller makes an errant grasp prediction, though, the user must open the hand fully before attempting the intended grasp again. These errant predictions tend to be attributed to two sources: the movement and position of the wrist, and the ability for a user to repeatedly perform a given grasp with minimal variation. To avoid the unintentional reopening of the hand and consequent user frustration, it is critical for the classifier to predict the proper grasp on the first attempt. In our previous study, we proposed a modification to the way data are windowed during real-time control to take advantage of the partial-hand prosthesis control scheme. By basing predictions on more data when selecting a grasp, users were

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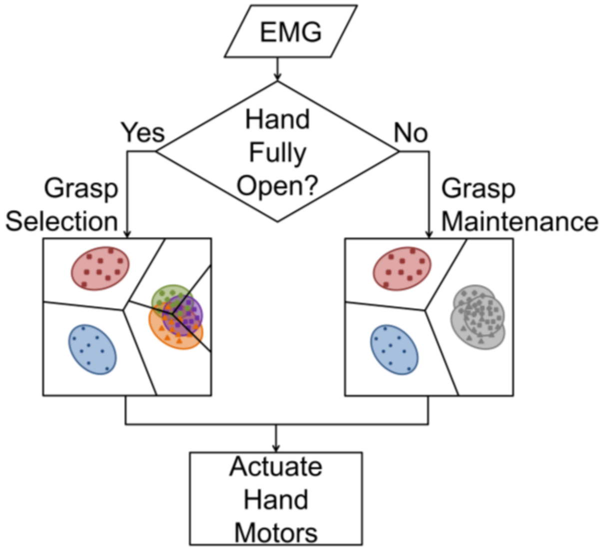

Figure 1. Prosthetic hand control flowchart. When the hand is fully open, the LDA classifier must select between *no movement*, *hand open*, and one of *N* hand-grasps (grasp selection). The use of a longer feature extraction window reduces class variance and, therefore, increases inter-class separability. If a grasp has been selected and the hand is not fully open, all *N* hand-grasps are mapped to *hand close*, and the classifier selects between these three classes (grasp maintenance). Because all hand-grasps are mapped to a common class, a shorter feature extraction window can be used to reduce system delay. Reproduced from [19].

able to select the intended grasp more often while performing a virtual prosthesis task [19]. We also developed two customizations (see Section II A) to the pattern recognition processing loop aimed at preventing errant predictions during grasp selection. Although these customizations improved usability and performance during virtual prosthesis tasks, it is unclear whether difficulties performing some of the tasks were attributed to wrist movements or the hand-grasp required to complete the task.

In this study, we compared offline classification errors and real-time performance metrics between wrist positions and between grasps to determine how each affects performance. We also determined how our proposed pattern recognition customization is impacted by the wrist position and hand-grasp required to complete a given task. We hypothesized that certain wrist positions and grasp patterns would result in real-time performance mal-effects. Furthermore, we hypothesized that our proposed customizations would suffer less from these mal-effects than the baseline controller. These results will help guide future efforts to design simple, intuitive, and responsive control systems for partial-hand prostheses.

II. Methods

A. Experimental Protocol

Nine non-amputee subjects participated in this study, which was approved by the Northwestern University Institutional Review Board. Informed written consent was obtained from all subjects prior to beginning the study. Subjects were a mix of novel users with no pattern recognition control experience, and users with prior experience controlling virtual prostheses. Twelve self-adhesive bipolar surface Ag/AgCl EMG electrode pairs were placed on the arm and hand; eight electrode pairs covered the extrinsic hand muscles in the forearm, and four electrode pairs covered the intrinsic hand muscles located in the hand, and reference electrode was placed over the lateral epicondyle of the humerus. The hand and forearm were wrapped with an elastic cohesive bandage to prevent electrode shifts. Subjects were seated in front of a computer monitor displaying a custom virtual interface [see Fig. 2].

The experimental protocol performed by subjects is explained in detail in [19] and is summarized here. Briefly, to train the classifier, subjects were asked to initiate and maintain each hand posture (relaxed hand, hand open, key grip, chuck grip, power grip, fine pinch) with the wrist in the neutral position (while seated, palms facing medially). Subjects also performed trials in which they maintained each hand posture while moving the wrist along trajectories about each of the three degrees of freedom (wrist/flexion extension, radial/ulnar deviation, and pronation/supination). An example trajectory is as follows: the user initiated a grasp in the fully-flexed wrist position and held this position for 2 seconds, then moved the wrist to the fully-extended position for 2 seconds, waited for 2 seconds, and returned the wrist to the flexed position over the last 2 seconds. Each trajectory lasted for 8 seconds and a visual aid for the desired trajectory was presented to the user within a graphical user interface. While being guided through each trajectory, data were collected and labeled to be used later in offline analyses and to train controllers for the real-time experiment.

During the real-time virtual prosthesis task, subjects were directed by a visual prompt to position their wrist in one of seven wrist positions: neutral, flexion, extension, radial deviation, ulnar deviation, pronation, or supination. A virtual

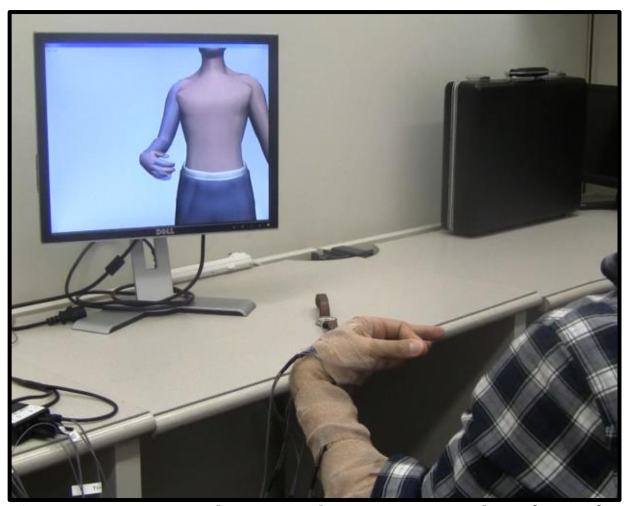

Figure 2. Experimental setup. Subjects were seated in front of a computer monitor displaying a custom virtual interface. During data collection for classifier training, the screen displayed the grasp to be maintained as well as a visual guide to assist the subject in performing the required wrist trajectory. During the real-time experiment (shown), the screen displayed a virtual wrist and hand as well as text to guide subjects through the experiment. Once the virtual hand was revealed at the beginning of each trial, control of the hand was relinquished to the subject. The on-screen text displayed which position to maintain the wrist during that trial, the grasp required to complete the task, and the grasp the virtual hand was currently selecting. The hand turned green to indicate successful task completion, and turned yellow to indicate a trial timeout.

hand was then revealed on the screen, control of the hand was released to the subject, and they were prompted to fully close the virtual hand in one of four grasps: key grip, chuck grip, power grip, or fine pinch. Subjects had 15 seconds to complete the task, after which the trial was marked as "timed out" and the subject moved to the next task. In addition to controlling the virtual hand with (1) a baseline pattern recognition system (see Section II B), two linear discriminant analysis (LDA) customizations were also tested: (2) a classification delay after the hand was determined to be in the fully-open position was imposed, and (3) a majority voting scheme using the most common in a set of consecutive predictions (i.e. the mode of the predictions) as the classification output [10]. The baseline LDA was windowed with a static 250ms windowing scheme, and the two proposed customizations used a dual-windowing scheme that windowed at 500ms when the user was attempting to select a grasp, and 200ms otherwise.

B. *Signal Processing*

EMG signals were sampled at 1000 Hz with a 30-350 Hz bandpass filter using TI ADS1298 biosignal amplifier chips. Data were windowed with a 25ms frame increment [10]. Time-domain and auto-regressive features were extracted, and an LDA was used to classify the resulting feature vector. For the classification delay customization (2), predictions were delayed by half of the current window length, and for the majority voting customization (3), the majority voting window was equal to the current window length.

C. *Data Analysis*

In our offline analysis, the data used to train the real-time classifier were tested via leave-one-trial-out cross-validation, using classification error rate (percentage of incorrect class predictions) to evaluate performance. Data from all wrist positions and movements were used to train an LDA classifier, which was then tested against data collected (1) only in the neutral wrist position, (2) during the wrist flexion/extension trajectory, (3) during the radial/ulnar trajectory, and (4) during the wrist pronation/supination trajectory. Results were also broken down to determine the classification error rate for each trained grasp. Each of these tests was performed with the data windowed into (1) 250ms windows and (2) 500ms windows. These are the window lengths associated with selecting a grasp in the real-time experiment with either the static window or dual-window classifier, respectively.

For analysis of the virtual prosthesis task, timeout rate and number of grasp selection attempts were used as performance metrics. Timeout rate was defined as the percentage of trials that were not completed within 15 seconds, and selection attempts was defined as the number of times a subject selected a grasp from the *hand open* position. If an undesired grasp was selected for a task, the subject had to fully open the virtual hand to attempt to select the desired grasp. The timeout rate and selection attempts were compared across two independent factors: the wrist position required for a task, and the grasp required for task completion.

D. *Statistical Analyses*

Analyses of variance (ANOVAs) were used for statistical analysis of the offline experiment, with the window length and either tested wrist position or tested hand-grasp pattern as fixed factors, and subject a random factor. Pairwise comparisons were made using a Bonferroni correction factor, and the significance level was set at $\alpha=0.05$. Post-hoc statistical analyses were performed for the real-time experiment. For each analysis, two independent tests were performed: one of the baseline pattern recognition system (unmodified LDA, static window), and one of a proposed customization (LDA with classification delay, dual windowing). Each was run through a two-way ANOVA, with either wrist task or grasp task as a fixed factor, and subject as a random factor. Data were normalized with a Box-Cox transformation [20]. Pairwise comparisons were made using a Bonferroni correction factor, and the statistical significance level for the ANOVA was set at $\alpha=0.05$.

III. Results

A. *Offline Experiment*

1) *Influence of the Wrist*

When comparing between wrist positions, offline classification error rates were lowest when classifying data collected when the wrist was in the neutral wrist position (pooled means, 4.3%) (pairwise, $p<0.05$) [see Fig. 3(a)]. Pooled error rates when classifying data collected during radial/ulnar deviation trajectories (11.9%) were higher than pooled error rates from classifying data collected during wrist pronation/supination trajectories (7.9%, $p<0.05$) and in the neutral wrist position ($p<0.001$).

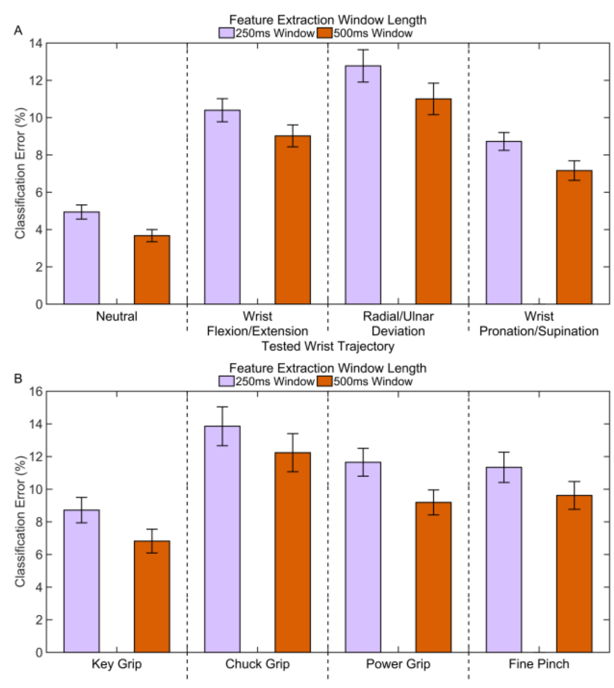

Figure 3. Offline classification error rate of real-time classifier training data. (a) Classification error by tested wrist trajectory. (b) Classification error by tested hand-grasp pattern. Error bars represent standard error.

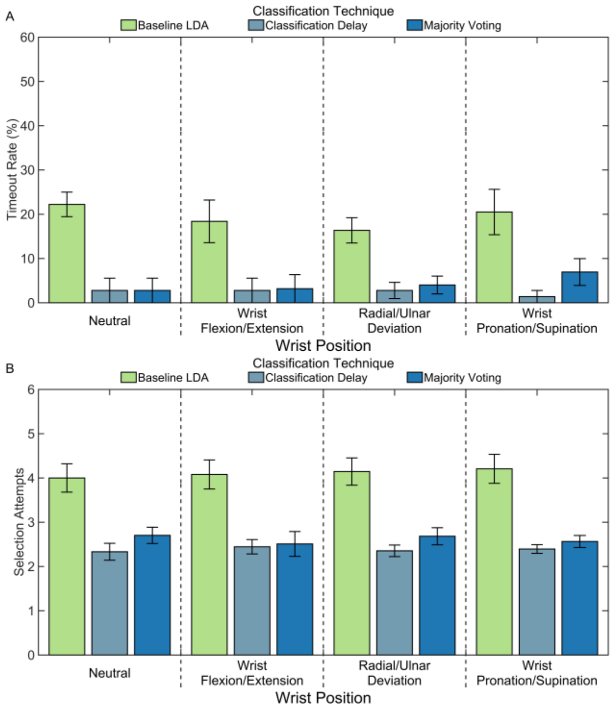

Figure 4. Influence of the wrist on virtual prosthesis task performance. (a) Timeout rate by required wrist position. Timeout rate is defined as the percentage of trials not completed within 15 seconds. (b) Selection attempts by required wrist position. A selection attempt is defined as the number of times a subject selected a hand-grasp from the *hand open* position. Error bars represent standard error.

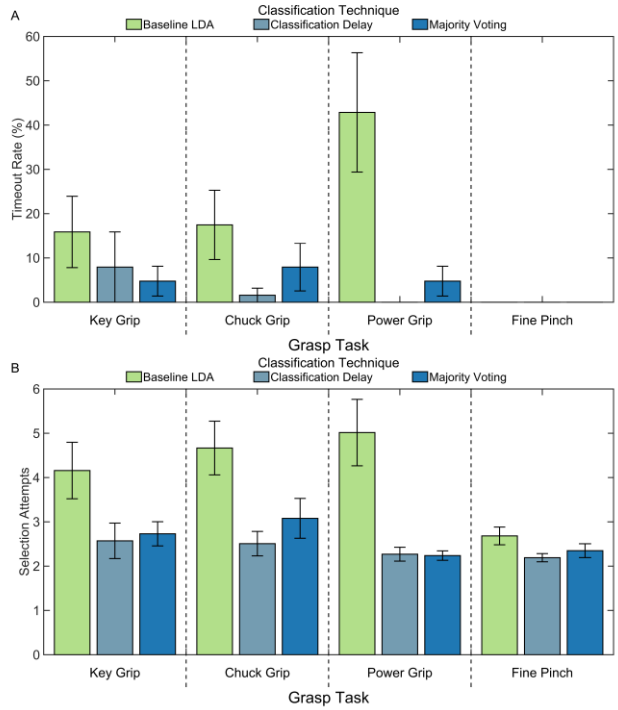

Figure 5. Influence of grasp on virtual prosthesis task performance. (a) Timeout rate by required grasp. Timeout rate is defined as the percentage of trials not completed within 15 seconds. (b) Selection attempts by required grasp. A selection attempt is defined as the number of times a subject selected a hand-grasp from the *hand open* position. Error bars represent standard error.

2) Influence of Grasp

There were no statistically significant differences between classification error rates of the hand-grasps (p=0.135) [see Fig. 3(b)]. Pooled error rates ranged from 7.7% to 13.0%, averaging approximately 10% error for all grasps.

3) Influence of Window Length

The 500ms window associated with the dual-window classifier yielded a lower pooled error rate (7.7% in wrist analyses, 9.5% in grasp analyses) than the 250ms window (9.2% in wrist analyses, 11.4% in grasp analyses), though neither difference was statistically significant (p=0.098 and p=0.220, respectively).

B. Real-Time Experiment

1) Influence of the Wrist

When the real-time experiment timeout rates were separated by required wrist position for virtual prosthesis task completion, there was no significant effect of wrist position found for the baseline pattern recognition system (p=0.575), classification delay (p=0.754), or majority voting (p=0.493) [see Fig. 4(a)]. Average timeout rates for the baseline pattern recognition system ranged from 16.4% to 22.2%, and the average timeout rates for the classification delay and majority voting customizations ranged from 1.4% to 2.8% and 2.7% to 6.9%, respectively.

Similar trends are seen with the selection attempts. The average number of attempts required by subjects to successfully complete a task did not vary significantly between wrist positions for the baseline system (p=0.953), classification delay (p=0.610), or majority voting (p=0.459) [see Fig. 4(b)]. Average baseline system selection attempts ranged from 4.0 to 4.2, classification delay selection attempts ranged from 2.3 to 2.4, and majority voting selection attempts ranged from 2.5 to 2.7.

2) Influence of Grasp

When separating timeout rates by the hand-grasp pattern required for task completion, some differences were found [see Fig. 5(a)]. For the baseline pattern recognition system, the average timeout rate was significantly higher for power grip (42.9%) than for fine pinch (0.0%, p<0.05). By comparison, average timeout rates for both the classification delay and majority voting customizations ranged from 0.0% to 7.9%, but neither was significantly affected by the grasp required for a task (p=0.476 and p=0.429, respectively).

Although it appears that subjects required more selection attempts on average to achieve power grip (5.0) than fine pinch (2.7) with the baseline system, this difference is not significant (p=0.056) [see Fig. 5(b)]. For the classification delay, average selection attempts ranged between 2.2 and 2.6, with no significant difference found between grasp tasks (p=0.827); for the majority voting customization, average selection attempts ranged between 2.2 and 3.1, but differences between grasp tasks were not significant (p=0.171).

IV. Discussion

Although myoelectric prostheses have recently become commercially available to partial-hand amputees, there are still many challenges to controlling these devices that must

Table 1. Summary of real-time experiment results. Wrist task and grasp task columns indicate influence of the wrist position and grasp required to complete a task on the timeout rate and selection attempts for that task. For each classification technique, the range is the minimum and maximum average value for a given metric, and the main effect *p*-value is calculated via the two-way ANOVA. Bolded *p*-values indicate $p<0.05$.

Classification Technique		**Wrist Task**		**Grasp Task**	
		Timeout Rate	***Selection Attempts***	***Timeout Rate***	***Selection Attempts***
Baseline LDA	Range	16.4% 22.2%	4.0 4.2	0.0% 42.9%	2.7 5.0
	Main Effect *p*-Value	0.575	0.953	**0.023**	0.056
Classification Delay	Range	1.4% 2.8%	2.3 2.4	0.0% 7.9%	2.2 2.6
	Main Effect *p*-Value	0.754	0.610	0.476	0.827
Majority Voting	Range	2.7% 6.9%	2.5 2.7	0.0% 7.9%	2.2 3.1
	Main Effect *p*-Value	0.493	0.459	0.429	0.171

be addressed before they are widely accepted. For many, partial-hand prostheses do not offer sufficient functionality to justify their purchase and use. A major contributor to this is their control method; because these devices are typically controlled in the same manner as transradial prostheses, they do not take into account control challenges of partial-hand amputees, including facilitating wrist movement and the need for multiple prehensile patterns. Our research has focused on this issue by developing training methods and control algorithms specifically for partial-hand prostheses [19].

In this study, we further evaluated these LDA customizations to show how their performance depends on both the wrist position and the hand-grasp pattern required for a given task. In the offline evaluation of subject training data, we show that the wrist position can affect classification error, but that the classified grasp does not have a discernable effect on the error. However, when considering results from the real-time experiment, we show that the wrist position required to complete tasks does not have a clear effect on either the timeout rate or the number of selection attempts made by the user. Instead, the required grasp significantly impacts the performance of the user, especially when controlling a virtual prosthesis with the baseline LDA. Both the classification delay and the majority voting customizations reduced timeout rates and selection attempts when compared to the baseline LDA [19]. In doing so, these customizations also drastically reduced the effect of desired grasp on performance; grasps that users had little trouble completing (such as fine pinch) only experience a small improvement, whereas grasps that users found difficult to select (such as power grip) experienced a much greater improvement, even so far as to match the performance of fine pinch.

The reason that the grasp required to complete a task had a greater effect than the required wrist position is likely because hand posturing is more difficult to do repeatedly. Pattern recognition classification requires novel data to be similar to the data on which the classifier initially trained. However, if a user cannot easily perform the same grasp with minimal variation, the predictive power of the classifier is expected to deteriorate. In addition to variations while the hand is fully-closed, there is likely greater variation while moving from an open or rest posture to the desired grasp. By implementing the classification delay and majority voting techniques, users are given an opportunity to complete this hand movement before a grasp prediction is made. This, in turn, allows users' EMG to "settle" and reduces its variation, thereby improving its discrimination from other grasps. This effect is illustrated by the lack of significant differences in timeout rate and selection attempts between different grasps.

Although this study focuses on partial-hand prostheses, these results may be transferable to multi-articulate hands designed for transradial prostheses as well. At the transradial level, the wrist can no longer move and interfere with grasp predictions (with the exception of simultaneous control of the wrist and hand movements of a transradial prosthesis [21]), but EMG also can no longer be collected from the intrinsic hand muscles, which would normally reduce classification errors of grasps [22]. We expect that our proposed classification delay and majority voting techniques would improve a user's ability to perform tasks requiring a specific grasp; however, this remains to be tested.

V. Conclusion

In order to provide the greatest functionality, partial-hand amputees must be able to fully control their prosthesis. Preserving the mobility of the wrist is a key design consideration for creating and controlling partial-hand prostheses. Additionally, permitting control of multiple hand-grasp patterns allows for greater flexibility and ability when performing daily tasks. We have shown that providing classifiers examples of grasps in multiple wrist positions can improve the control system's ability to discern grasps in different wrist positions in real-time, but additional steps are required to facilitate hand-grasps that users find difficult to execute. Our proposed LDA customizations were shown to reduce the variability of performance based on grasps required to perform a task, therefore making previously difficult grasps viable options for performing daily tasks and allowing for a greater flexibility in how these tasks are completed.

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