The effect of powered prosthesis control signals on trial-by-trial adaptation to visual perturbations

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***Abstract*— Powered prostheses have the potential to restore abilities lost to amputation; however, many users report dissatisfaction with the control of their devices. The high variability of the EMG signals used to control powered devices likely burdens amputees with high movement uncertainty. In able-bodied subjects uncertainty affects adaptation, control, and feedback processing, which are often modeled using Bayesian statistics. Understanding the role of uncertainty for amputees might thus be important for the design and control of prosthetic devices. Here we quantified the role of uncertainty using a visual trial-by-trial adaptation approach. We compared adaptation behavior with two control interfaces meant to mimic able-bodied and prosthesis control: torque control and EMG control. In both control interfaces, adaptation rate decreased with high feedback uncertainty and increased with high mean error. However, we did observe different patterns of learning as the experiment progressed. For torque control, subjects improved and consequently adapted slower as the experiment progressed, while no such improvements were made for EMG control. Thus, EMG control resulted in overall adaptation behavior that supports Bayesian models, but with altered learning patterns and higher errors. These findings encourage further studies of adaptation with powered prostheses. A better understanding of the factors that alter learning patterns and errors will help design prosthesis control systems that optimize learning and performance for the prosthesis user.**

I. INTRODUCTION

Powered upper limb prostheses have a high rate of abandonment, and many amputees rely instead on body-powered prostheses, or no prosthesis at all [1]. Users report that powered prostheses lack dexterity and that coordinated movements are difficult or impossible [2]. One source of difficulty may be the highly variable nature of the electromyographic (EMG) signals [3], which can make users uncertain of how the arm will respond. To guide improvements to prosthesis control and feedback, we need to understand how EMG control and uncertainty affects movements with prostheses.

In able-bodied subjects, uncertainty affects adaptation [4], control [5], and feedback processing [6]. Bayesian models typically formalize adaptation as a problem of estimating the relevant dynamics [7]. These models make concrete predictions of the factors that influence adaptation. Adaptation should be fast when sensory information is precise and the subject is uncertain of movement outcomes. Conversely, adaptation should be slow when sensory information is uncertain and the subject is confident in movement outcomes. The important point about this line of research is that it allows us to use adaptation studies to implicitly measure uncertainty, which is crucial for control, learning and coordination.

Prosthesis control likely introduces higher uncertainty, due in part to the high variability of EMG signals and the lack of kinesthetic feedback [8]. These conditions may hinder the prosthesis user's ability to adapt in response to errors. To improve the interaction between the person and the prosthesis, we want to understand how uncertainty affects prosthesis control. Uncertainty and its role in adaptation influences the type of control systems that will most effectively improve performance.

To begin characterizing adaptation with powered prostheses, we used an established experimental paradigm [4], [9], [10] in which perturbations test the user's reliance on feedforward and feedback information. We studied trial-by-trial adaptation to visual perturbations with two levels of feedback uncertainty. We compared adaptation rates and mean errors with two control interfaces: torque and EMG, which serves as a simplified comparison between able-bodied and prosthesis control signals. Subjects used the same isometric setup for both interfaces, allowing for a meaningful comparison of adaptation.

II. METHODS

A. Subjects

Eight able-bodied subjects participated in this study. Three subjects were female, five were male, and all were between 23 and 32 years old. The experiment was approved by the Northwestern University Institutional Review Board.

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B. Experimental Protocol

The experiment was designed to assess the balance between relying on feedforward state predictions and relying on feedback information. The subject moved a cursor in the absence of feedback, and presumably had some prediction of the movement endpoint. We then show perturbed visual feedback of the endpoint. The subject's corrective action on the following trial indicates some adaptation to the perceived error. The average portion of the error that is corrected is referred to as the adaptation rate.

Subjects used elbow extension to move a cursor towards a target along a single degree-of-freedom (DOF) circular track (Fig. 1). Movement time was limited to 3 seconds, after which the cursor returned to the starting position. Subjects were given 10 practice trials, in which they had visual feedback of the cursor throughout the movement. In a second round of 15-20 practice trials, visual feedback was removed 0.5 seconds into the movement time and reappeared after the movement for 100 ms to show the subject the cursor endpoint [4], [11]. This terminal visual feedback allowed the subjects to see their error at the end of the trial, but minimized any corrective movements during the trial. The testing phase of the experiment consisted of 4 blocks of 75 trials each, with approximately 2 minutes of resting between blocks. In this phase, the cursor endpoint was perturbed visually by either -40, 0, and 40 degrees. Subjects were not informed of the perturbations and were instructed to hit the target as accurately as possible.

To manipulate feedback uncertainty, the cursor endpoint was randomly displayed as either one dot or five dots [4], [12]. Feedback uncertainty was low when subjects saw the cursor as one dot, whereas feedback uncertainty was high when subjects saw the cursor as five dots. The spread of the five dots was a Gaussian distribution with the true cursor position as the mean and a standard deviation of 40 degrees.

C. Control Interfaces

Subjects completed the experimental protocol once with torque and once with EMG, with each protocol on separate days in a randomized order.

For both the torque and EMG control interfaces, subjects placed their right arm in a modified elbow brace that minimized movement (ProCare Elbow RANGER Motion Control). A reaction torque sensor measured elbow extension torque (Futek TFF40). A self-adhesive bipolar electrode measured the EMG of elbow extension (Delsys Bagnoli).

The effort level required to control the cursor was equalized as closely as possible across torque and EMG control. Subjects exerted approximately 4 N-m of extension torque for 10 seconds using visual feedback as guidance. The mean absolute value of torque and EMG activity were recorded and used to normalize torque and EMG control signals to the same contraction strength. The control signals were high-pass filtered at 0.1 Hz, rectified, low-pass filtered at 5 Hz, normalized, and mapped to cursor velocity [13]. Dynamics were chosen to match those of a typical prosthetic arm [14].

Figure 1. Illustration of experimental setup. The cursor started at the left side of the circle (grey dot). Subjects used either elbow extension torque or elbow extension EMG activity to move the cursor clockwise towards the target (green square). The cursor endpoint was shown as either one dot or five dots (shown above) to manipulate feedback uncertainty.

III. Results

We compared trial-by-trial adaption to visual perturbations across two control interfaces—torque and EMG—with two levels of feedback uncertainty each. Feedback uncertainty was manipulated by displaying cursor feedback as one dot (low uncertainty) or as five dots (high uncertainty). Overall adaptation rate was evaluated as a function of control interface, feedback uncertainty, and mean absolute endpoint error. Adaptation rate and mean error were also calculated over each block to assess changes over the course of the experiment.

Each subject displayed trial-by-trial adaptation during both torque control and EMG control (Fig. 2). A visual perturbation in one direction typically elicited a correction in the opposite direction on the following trial. The average

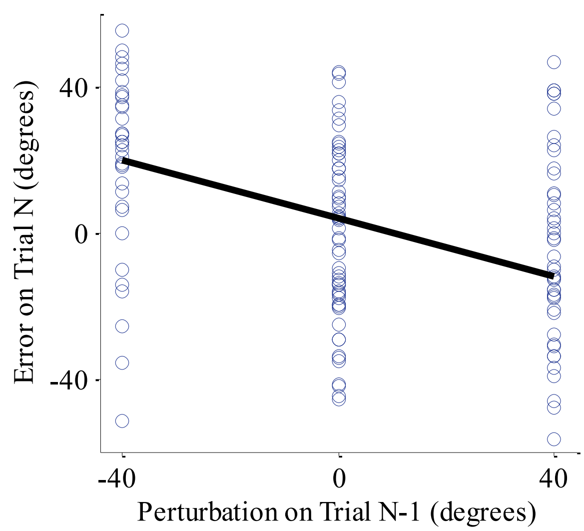

Figure 2. Data from representative subject using EMG control. Each circle represents an individual trial. Adaptation rate is calculated as the slope of the regression line (bold solid line) between the endpoint error of trial N and the perturbation on trial N-1. Trials following one-dot terminal feedback were separated from those following five-dot terminal feedback and adaptation rate was calculated separately for each feedback condition (one-dot condition shown). Note: the slope of each regression is negative; however, adaptation rates are reported as positive numbers.

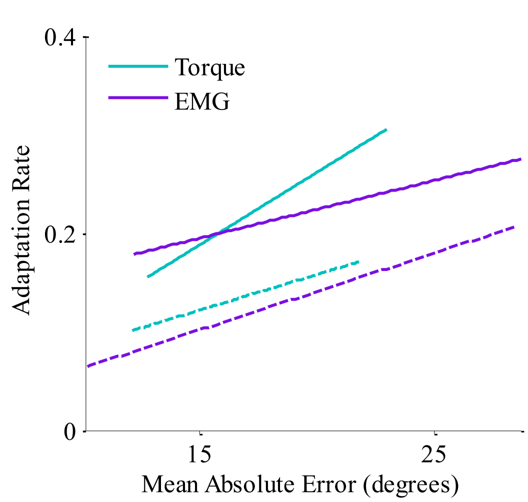

Figure 3. Adaptation rate as a function of mean absolute endpoint error. Solid lines indicate low feedback uncertainty (one dot) and dashed lines indicate high feedback uncertainty (five dots).

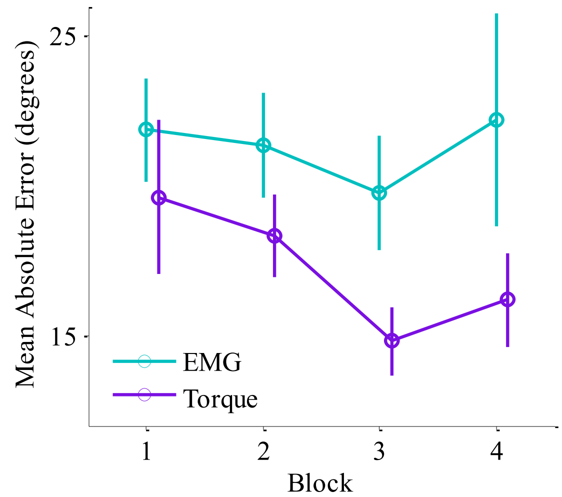

Figure 4. Mean absolute endpoint error as experiment progressed. Bars indicate standard errors of the mean. One block includes 75 trials.

amplitude of the correction response, or the slope of the regression between error(n) and perturbation(n-1), is a measure of adaptation rate. The slope of each regression was negative, indicating positive adaptation rate.

Overall adaptation rate increased as mean error increased, but was not significantly affected by control interface (Fig. 3). The slope of the relationship between adaptation rate and mean absolute endpoint error was statistically significant (*$p<0.02$,* Table 1). Higher feedback uncertainty significantly decreased the intercept of this relationship (*$p<0.01$,* Table 1). Control interface did not have a statistically significant effect on either the intercept (*$p=0.66$,* Table 1) or the slope (*$p=0.53$,* Table 1) of the relationship between adaptation rate and mean error.

In the first block of trials, the mean error of EMG control was not significantly different that of torque control; however, in blocks two through four, the mean error of EMG was significantly higher (Figure 4). The mean error of torque decreased as the experiment progressed (from block two to three), whereas the mean error of EMG control did not significantly change across all four blocks.

In the one-dot feedback condition, adaptation rate decreased as the experiment progressed for torque control, but did not change significantly for EMG control (Fig. 5, top). In the five-dots feedback condition, there were no statistically significant changes in adaptation rate for EMG or torque control (Fig. 5, bottom).

TABLE 1. RESULTS OF THREE-WAY ANOVA ON ADAPTATION RATE.

Factor	Type	p-value
Feedback uncertainty	Categorical	<0.01
Control signal	Categorical	0.66
Mean error	Continuous	<0.02
(Control signal)*(Mean error)	Continuous	0.53

Categorical factors indicate an offset change to adaptation rate.
Continuous factors indicate a slope change to adaptation rate.

IV. DISCUSSION

In this work we compared trial-by-trial adaptation with torque and EMG control interfaces. We found that the control interface did not significantly affect overall adaptation rate, and instead that adaptation rates depended primarily on mean error and on feedback uncertainty. Only for the torque condition did we see a decrease in error over time and a concomitant decrease in adaptation rate.

Subjects displayed clear adaptation using EMG control (Fig 4), which encourages further characterization of adaptation during prosthesis control. Previous studies have suggested that prosthesis users are capable of adaptation, but very few have explicitly investigated sensorimotor adaptation. Amputees have intact central nervous system capabilities and those that use myoelectric prostheses experience only minimal cortical reorganization after amputation [15]. Goal-directed reaching capabilities for amputees using body-powered prostheses are not significantly different from able-bodied subjects [16]. Able-bodied subjects using EMG control are able to adapt to unintuitive control schemes with only visual feedback [17]. These studies all imply that prosthesis users maintain adaptation capabilities, and our results confirm this theory.

However, this study is only a small first step towards understanding the sensorimotor adaptation of amputees. Here we studied able-bodied subjects using EMG control in a single-DOF task. Multi-DOF tasks and multi-site control schemes present more complex challenges. Amputees using physical prostheses also face more complex challenges, and it's unclear how the dynamics of the prosthesis and the control scheme will affect adaptation.

The overall adaptation rates were not significantly different between torque and EMG control (Fig. 3, Table 1); however, we observed different error patterns (Fig. 4) and learning patterns (Fig. 5) across individual blocks of the experiment. The mean error of EMG was higher and stayed fairly constant, whereas the mean error of torque decreased over time. The error is a function of both random variability

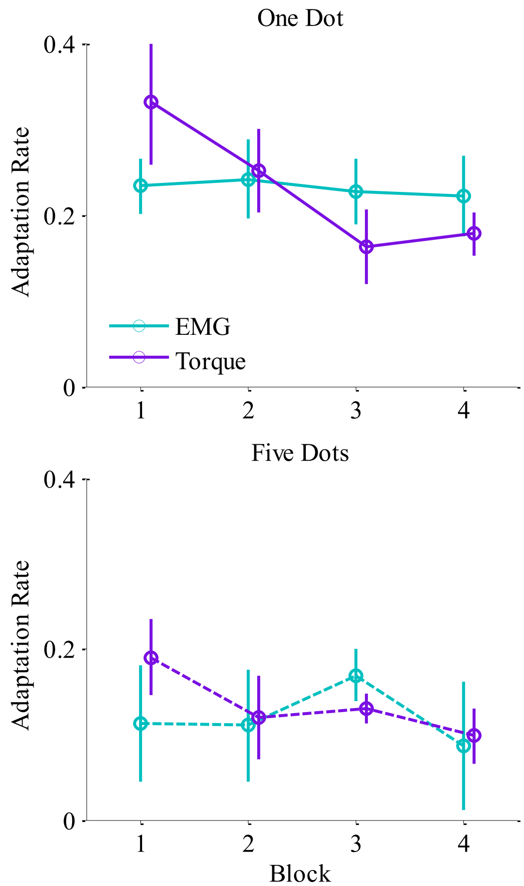

Figure 5. Adaptation rate as experiment progressed. The top plot shows adaptation in the one dot, or low feedback uncertainty condition. The bottom plot shows adaptation in the five dots, or high feedback uncertainty condition. Bars indicate standard errors of the mean. One block is 75 trials.

in the signal and of operator error, and the patterns we observed may be caused by the higher variability of EMG signals. Subjects were able to reduce operator errors and improve performance with torque control, but may have been limited by the higher variability with EMG.

Our overall results support Bayesian predictions and previous findings [4] with regards to both feedback and feedforward uncertainty. As feedback uncertainty increased from one dot to five dots, adaptation rates decreased (Fig. 3). As mean absolute error increased, adaptation rates increased. If we assume that mean absolute error is an indication of feedforward uncertainty, this follows the Bayesian prediction that feedforward uncertainty speeds up adaptation. Thus we suggest that Bayesian models are appropriate for describing adaptation during prosthesis control and that future studies should explore more complex tasks.

Our block-by-block analysis showed altered learning patterns and higher error rates with EMG control. These differences may be caused by the variability of EMG control signals, slower learning timescales, suboptimal control dynamics, or other factors. We need a closer examination of the factors that influence learning patterns with EMG control, because altered learning patterns may contribute the lack of coordination experienced by amputees using powered prostheses.

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