Effects of Mapping Uncertainty on Visuomotor Adaptation to Trial-By-Trial Perturbations with Proportional Myoelectric Control

Kenneth R. Lyons, *Student Member, IEEE* and Sanjay S. Joshi, *Senior Member, IEEE*

***Abstract*— Myoelectric control based on classification of distinct gestures discretizes the output space available to the user, which can make it difficult to react appropriately to novel scenarios such as changing limb position. While proportional myoelectric control is noisy in comparison to pattern recognition control, this noise may be an important component of skill acquisition. Here we implemented a two-dimensional proportional myoelectric controller to investigate the effects of movement direction and mapping uncertainty on adaptation to trial-by-trial perturbations. We found that subjects who practiced hitting targets despite trial-by-trial random modifications of the control mapping adapted to perturbations faster than a control group with low mapping variability. Our findings suggest that exposure to a variable mapping encourages exploratory behavior and underlies a change in adaption rate, which could potentially be used to train myoelectric control users to achieve more robust control.**

I. INTRODUCTION

Surface electromyography (EMG) is a non-invasive sensor modality that can enhance the ability of individuals with different kinds of disabilities to interact with the environment, such as amputees controlling powered prosthetic limbs or paralyzed individuals controlling communication interfaces. Much of the current work on myoelectric control uses gesture classification to discretize the output and provide intuitive and low-noise control of a number of commands [1]. Proportional control, in which EMG signal amplitudes directly influence dynamic parameters of the object under control, offers control that is more similar to our natural movements, but at the cost of much noisier output [2]. We seek to leverage insights from human motor learning and control to study how users of myoelectric control interfaces learn to manipulate EMG signals to achieve desired outcomes. Ultimately, our aim is to design or discover training strategies that improve control reliability and robustness despite various nonstationarities inherent in myoelectric control such as the limb position effect [3], muscle fatigue, and electrode shift.

One concept from motor learning that has recently been studied with myoelectric control is the notion of an adaptation rate, describing the proportion of an error the subject corrects for in the subsequent trial or trials. The Bayesian integration model of visuomotor adaptation is one model of this behavior, predicting that the amount by which we adjust our reaching movements after being presented with a perturbation depends on sensory uncertainty as well as the variability of past experiences performing reaching movements [4]. The model predicts that increased sensory uncertainty results in more reliance on a forward model to form an estimate of state, such that when a perturbation is suddenly applied, the blurred feedback is treated as unreliable and the subject doesn't adjust to the perturbation. This behavior has been demonstrated in a planar reaching tasks with step perturbation [5] as well as trial-by-trial random perturbation [6], where the adaptation rate is defined as the proportion of the perturbation seen in trial $k-1$ corrected for in trial k. It has also been shown that displaying randomly scattered feedback in a one-dimensional myoelectric control task leads to reduced adaptation to trial-by-trial perturbations [7]. The other main prediction of the Bayesian integration model is that increased model uncertainty, whether it arises from motor noise or modeling errors, *increases* our reliance on feedback because our forward model predictions are not trustworthy. This has been demonstrated less robustly than the effect of sensory uncertainty [8], but there is at least some evidence that there is an effect through direct or indirect modifications of model uncertainty [5], [6], [9].

Several questions remain open regarding model uncertainty and the effects on sensorimotor learning. In the case of myoelectric control specifically, it is unclear if adding additional uncertainty to an already noisy control interface could drive a change in adaptive behavior. It is also not known whether an increased tendency to adapt to perturbations is *useful*, as it fundamentally means a forward model is not well formed or is not trusted. An alternative view is that uncertainty in the mapping is a mechanism by which one learns this forward model, which produces better long-term performance [10], [11]. One example of the intentional addition of control signal variability driving favorable behavior comes from Thorp et al., who showed that applying noise to only a subset of a redundant control system's inputs results in subjects avoiding use of those inputs [12]. This kind of intervention could be used in training procedures to reduce the reliance on dominant inputs and promote exploration of less-used input space.

In this study, subjects were exposed to a new form of mapping uncertainty in which the vertical components of a linear mapping between EMG signal amplitude and two-dimensional cursor position was randomized on every trial during a cursor-to-target familiarization task. A control group performed the same task, but without the mapping variability. After familiarization, the mapping was held fixed and subjects made movements to a target without feedback until the end of the movement, when a perturbed cursor position was shown briefly. We found that subjects in the mapping noise

*This work was supported by NSF grant 1208186

K. R. Lyons and S. S. Joshi are with the Department of Mechanical and Aerospace Engineering, University of California, Davis, Davis, CA, 95616. krlyons@ucdavis.edu, maejoshi@ucdavis.edu

group overall adapted faster to the perturbations, as predicted by the Bayesian integration model. These results suggest that adaptation rate can be driven by increased mapping uncertainty, which could be a useful mechanism for getting a user to explore the input space.

II. Methods

A. Experiment Setup

Twelve subjects participated in the experiment: 8 female and 4 male, 10 right hand dominant and 2 left hand dominant, 18 to 26 years old. The subjects were split into two groups of six: a noise group and a control group. All subjects were informed of and consented to procedures approved by the Institutional Review Board at UC Davis (protocol #943281).

Subjects were fitted with six wireless EMG sensors (Delsys Trigno system), placed approximately one third of the forearm length distal to the elbow on the dominant arm, which would be a reasonable sensor arrangement for a transradial amputee. The first two electrodes were placed on either side of the ulna, then the rest of the sensors were placed approximately equidistantly around the remaining space. Throughout the session, subjects were seated with the elbow resting on an arm rest with the arm held parallel to the floor and pronated so the palm faced downward. Subjects were instructed to keep the forearm still and move only the wrist.

In all experimental tasks, subjects viewed a computer screen with a square cursor interface drawn on it (26.8 cm wide). The center of the interface was marked with a small cross and the edges were defined to be one unit away from the origin in all four directions (normalized coordinate system). The cursor diameter was 0.04 units and the target diameter was 0.2 units. For the two left-handed subjects, the cursor interface was mirrored horizontally for all tasks so that the same wrist movements could be used by all subjects in the adaptation task.

The EMG signals were recorded at a sampling rate of 2000 Hz in chunks of 50 ms. These chunks were centered to have zero mean and then filtered with a fourth-order Butterworth bandpass filter with cutoff frequencies of 10 Hz and 450 Hz. Windows of 200 ms were then formed (150 ms overlap between adjacent windows) and the root mean square (RMS) of each channel in the window was computed to form a six-dimensional feature vector representing the magnitude of activation of each channel.

B. Experimental Tasks

1) Mapping: In the mapping task, the cursor automatically moved from the origin out to a target location and back while the subject aimed to follow this movement by moving the wrist. Eight targets, arranged in $45°$ increments around a circle 0.9 units from the origin, were presented once each in a block in random order. Seven blocks of trials were performed. Each trial started by displaying the cursor in the center and the target. The cursor held the position at the center for 1 s, moved out to the center of the target in a sinusoidal velocity profile over 2 s, remained in the target for 4 s, then returned to the origin. Subjects were instructed to follow the cursor's position as closely as possible by actuating the wrist in extension/flexion and radial/ulnar deviation (Fig. 1b), using a moderate amount of effort at the target position.

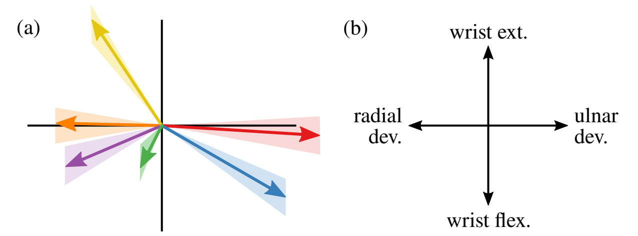

Fig. 1. (a) Cursor control mapping from a representative subject. Each arrow represents a single EMG channel's effect on the cursor position. For the noise group, new mappings were formed on each trial by perturbing the mapping vectors vertically. (b) Wrist movements subjects used to move the cursor in the four cardinal directions (assuming right hand dominant).

After completing the mapping task, the RMS values in each channel were scaled to the range $[0, 1]$. In subsequent tasks, the scaling factors were applied to the RMS values computed in real time, and the scaled values were put through an exponentially weighted moving average filter with a decay rate of 0.5. The scaled RMS features and corresponding cursor positions from the mapping task were fit to a linear model via ordinary least squares regression, producing a 2×6 matrix mapping scaled RMS values to a two-dimensional cursor position. This is referred to as the *base mapping*. An intercept term was not included in the regression since the inputs were scaled to $[0, 1]$. Scaling the features and fitting a model without an intercept enables applying modifications to the mapping without introducing bias—i.e. relaxing the arm with low muscular activity always places the cursor at the origin.

2) Familiarization: In the familiarization task, subjects used the proportional control scheme to move the cursor to targets as quickly as possible, with veridical feedback throughout the trial. Eight targets arranged in a circle were again presented one at a time, this time at 0.54 units from the center of the cursor interface (60% of the distance used in the mapping task). Each target was presented once per block in random order, and 10 blocks were completed. After the target was presented, the subject had 10 s to move the cursor to the target and dwell inside it for 500 ms, otherwise the trial timed out.

On each trial, the mapping matrix was formed by adding six samples (one for each channel) from a zero-mean Gaussian distribution to only the y component of each column of the base mapping, illustrated in Fig. 1. The variance of the distribution was set either to 0.01% (control group) or 1% (noise group) of the median magnitude of the columns of the base mapping matrix. This constituted the only difference between the control and noise groups. The intended effect of this mapping update was to change the effect of each EMG channel in the vertical direction only without directly affecting the subject's ability to hold the cursor in a small

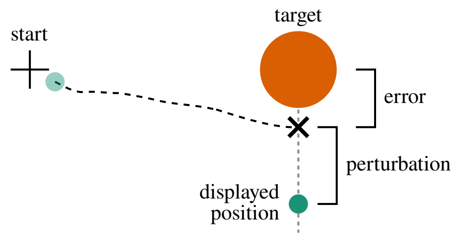

Fig. 2. Illustration of an adaptation trial to the target at 0°. The cursor begins at the starting location (center of the screen) then disappears as the subject moves in the target direction. Once the cursor passes an invisible line perpendicular to the target direction, its position is perturbed and displayed.

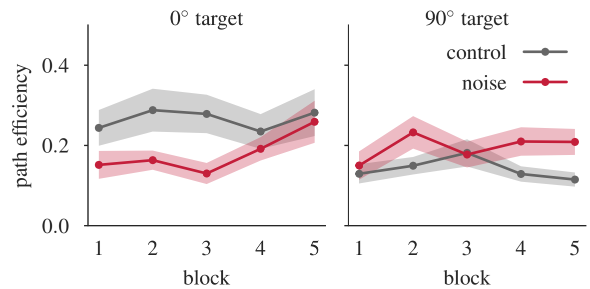

Fig. 3. Path efficiency by block in the familiarization task. Each block consists of two repetitions of each target. Points represent subject averages and filled regions represent ± one standard error of the mean.

region (as adding random input or output noise would). While the variance seems low, small changes to the input in the null space of the mapping matrix (i.e. different inputs leading to the same cursor position for the base mapping) can cause large variations in the vertical component of the cursor position once the mapping is changed.

3) Adaptation: In the adaptation task, only two targets were used: 0° and 90° (measured counterclockwise from the right). The cursor started in the center, then as it moved beyond 0.1 units from the origin, it disappeared so that subjects were required to move toward the target without feedback. Once the cursor passed through an invisible line perpendicular to the target direction at the target center, the cursor's position was perturbed along that line and the perturbed position was displayed for 1 s before returning to the center for the next trial. An illustration of a typical trial is shown in Fig. 2. Perturbations were randomly drawn from the set $\{-0.3, 0, 0.3\}$ units. The task proceeded in a block structure, where each block consisted of two repetitions of the three perturbations in random order, followed by a null trial in which the cursor's final position was not displayed. Each of the two targets were allocated 10 blocks in random order, for 140 trials total. Mapping perturbations were disabled for both groups in the adaptation task, since these would potentially introduce additional variability in the feedback.

C. Analysis

1) Path Efficiency: Cursor trajectories from the familiarization task were analyzed to uncover potential differences between groups as well as the two targets of interest in the adaptation task. One informative measure of control capability is path efficiency, defined as the ratio of the cumulative distance traveled over the course of a trial to the straight line distance to the final cursor position. It encapsulates both directness of the cursor trajectory and the ability to hold the cursor position steady once it reaches the target position. To analyze path efficiency over the course of the practice task, we combined blocks (as they were presented) such that each block contained two repetitions of each target instead of one.

2) Adaptation Rate: The trial-by-trial adaptation behavior was viewed through the lens of a Kalman filter [6], which is a special case of Bayesian integration. The subject's estimate of the target position on trial k is $\hat{x}_{k|k-1}$, and this is assumed to be directly recorded as the cursor position at the end of the movement (before perturbation is applied). Once the perturbation is applied and the feedback is received, the subject updates the estimate by applying the Kalman filter update:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k y_k \tag{1}$$

where K_k is the Kalman gain and y_k is the innovation, which is in our case the experimentally applied perturbation (the feedback position minus the true cursor position). Rearranging (1) and making the simplifying assumption that the dynamic model is unity, we get a relationship between the change in true cursor position from one trial to the next and the perturbation:

$$\delta_{k,k-1} = K_k y_k \tag{2}$$

The adaptation rate is then the coefficient of a linear regression fit to the true cursor position change versus the perturbation from the previous trial. Higher adaptation rate indicates a willingness to trust feedback over forward prediction. An adaptation rate was computed for each subject and each of the two targets (0° and 90°). A mixed effect analysis of variance (ANOVA) model was then used to test for differences between groups (random effects factor), target angle (fixed effects factor), and the interaction between the two. Significance was determined with $\alpha = 0.05$.

III. Results

A. Familiarization

Early in the experiment, we noticed that some subjects seemed to have more difficulty reaching and remaining inside the 90° target. This led to an analysis of the path efficiency during the familiarization task, which is shown in Fig. 3. As expected from our observations, the control group's path efficiency for the 90° target was lower. Furthermore, the noise group's motion to the 0° target was affected by the vertical trial-by-trial mapping perturbations introduced, giving indirect evidence that the magnitude of the mapping noise was sufficient to drive a change in behavior. Movement to the correct vertical location for the 90° target with a changing mapping should involve only minor adjustments to the strength of muscle contraction, whereas correcting

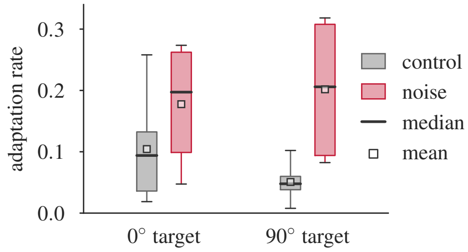

Fig. 4. Adaptation rates for the two groups and two targets in the adaptation task. Each subject's data for the given condition is averaged, then subject means are combined to form the boxes.

the vertical position out at the 0° target could require more complex manipulations. It appears from Fig. 3 that this is the only condition in which learning occurred over the course of the familiarization task.

B. Adaptation

Adaptation rates are shown in Fig. 4. The mixed effect ANOVA showed that group was a significant factor ($P = 0.026$), whereas the target angle and the interaction between group and target angle were not found to be significant ($P = 0.626$ and $P = 0.214$, respectively). Surprisingly, adaptation rates in the noise group tended to be higher for both targets, rather than only the 0° target. It was also unexpected to find such low adaptation rates in the control group, as compared to adaptation rates found in similar myoelectric control experiments with low feedback uncertainty [7].

IV. Discussion

Our main finding is that trial-by-trial changes in a linear, proportional myoelectric control interface's mapping during a familiarization phase led to increased adaptation rate, even though the mapping was fixed in the adaptation phase. We attribute this effect to the use of *mapping uncertainty* as opposed to adding random or signal-dependent noise to the cursor position during familiarization. Because the mapping itself changed from trial to trial, subjects were forced to produce different EMG activation profiles to achieve the same target. This caused the internal model of how motor commands influenced cursor position to be more uncertain and therefore less trustworthy than the feedback.

The secondary finding that the anisotropic (vertical only) mapping noise did not affect adaptation to the two target directions differently is somewhat surprising. In planar reaching experiments, He et al. showed that adaptation rate is higher for more distant targets because they are associated with decreased proprioceptive precision, hence subjects are more uncertain of their feedforward prediction and rely more on the previous trial's feedback [9]. In our case, perhaps the mapping uncertainty equalized control difficulty in both directions, whereas the control group tended to find the 0° target somewhat easier to reach and dwell inside. This doesn't, however, explain the lack of difference in adaptation rate between the two targets for the control group.

One limitation of our study design is that we did not block the subject's hand from sight. While the hand position or wrist angle does not necessarily correlate perfectly with cursor position, receiving this un-perturbed feedback could cause the adaptation rate to decrease, potentially explaining the low adaptation rates observed in the control group (or overall). Furthermore, the use of eight targets in the familiarization task likely reduced the effect of the mapping uncertainty overall. Another limitation is the small number of subjects (six per group). With relatively high variability between subjects in myoelectric control tasks, a larger sample would be appropriate for future work. Finally, a more thorough investigation of the mapping noise variance would help to more fully evaluate the Bayesian integration model.

While we have demonstrated the ability to modify adaptation behavior via a simple intervention potentially applicable to many myoelectric control schemes, the higher-level goal is to improve the ability of individuals with disabilities to interact with their environment, which becomes an issue of skill learning rather than adaptation. However, if mapping uncertainty is a mechanism through which exploratory behavior is encouraged, it may be possible to increase the robustness and reliability of myoelectric control through user training.

Acknowledgments

The authors thank Benjamin W. L. Margolis for helpful discussions during the development of this study and the software that implemented it.

References

[1] A. D. Roche, H. Rehbaum, D. Farina, and O. C. Aszmann, "Prosthetic Myoelectric Control Strategies: A Clinical Perspective," *Curr. Surg. Reports*, vol. 2, pp. 1–11, jan 2014.
[2] M. Ison and P. Artemiadis, "Proportional Myoelectric Control of Robots: Muscle Synergy Development Drives Performance Enhancement, Retainment, and Generalization," *IEEE Trans. Robot.*, vol. 31, no. 2, pp. 259–268, 2015.
[3] A. Fougner, E. Scheme, A. D. C. Chan, K. Englehart, and Ø. Stavdahl, "Resolving the Limb Position Effect in Myoelectric Pattern Recognition," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 19, no. 6, pp. 644–651, 2011.
[4] K. P. Körding and D. M. Wolpert, "Bayesian Integration in Sensorimotor Learning," *Nature*, vol. 427, no. 6971, pp. 244–247, 2004.
[5] J. Burge, M. O. Ernst, and M. S. Banks, "The Statistical Determinants of Adaptation Rate in Human Reaching," *J. Vis.*, vol. 8, no. 4, pp. 1–19, 2008.
[6] K. Wei and K. Körding, "Uncertainty of Feedback and State Estimation Determines the Speed of Motor Adaptation," *Front. Comput. Neurosci.*, vol. 4, no. 11, pp. 1–9, 2010.
[7] R. E. Johnson, K. P. Kording, L. J. Hargrove, and J. W. Sensinger, "Does EMG Control Lead to Distinct Motor Adaptation?," *Front. Neurosci.*, vol. 8, no. 302, pp. 1–6, 2014.
[8] J. W. Krakauer and P. Mazzoni, "Human Sensorimotor Learning: Adaptation, Skill, and Beyond," *Curr. Opin. Neurobiol.*, vol. 21, no. 4, pp. 636–644, 2011.
[9] K. He, Y. Liang, F. Abdollahi, M. Fisher Bittmann, K. Kording, and K. Wei, "The Statistical Determinants of the Speed of Motor Learning," *PLOS Comput. Biol.*, vol. 12, no. 9, pp. 1–20, 2016.
[10] H. G. Wu, Y. R. Miyamoto, L. N. G. Castro, B. P. Ölveczky, and M. A. Smith, "Temporal Structure of Motor Variability is Dynamically Regulated and Predicts Motor Learning Ability," *Nat. Neurosci.*, vol. 17, no. 2, pp. 312–321, 2014.
[11] A. W. Shehata, E. J. Scheme, and J. W. Sensinger, "The Effect of Myoelectric Prosthesis Control Strategies and Feedback Level on Adaptation Rate for a Target Acquisition Task," in *2017 Int. Conf. Rehabil. Robot.*, pp. 200–204, 2017.
[12] E. B. Thorp, K. P. Kording, and F. A. Mussa-Ivaldi, "Using Noise to Shape Motor Learning," *J. Neurophysiol.*, vol. 117, no. 2, pp. 728–737, 2017.