Simulating the Effects of Explicit Error-based Sensory Feedback on Motor Performance

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I. Introduction

Users may benefit from *explicit sensory feedback* when learning a new motor skill. This feedback, like auditory or visual direction from a coach, requires users to deliberately adjust their movements based on instructions. When learning a dance move or acquiring a medical skill, providing users with explicit feedback that is *error-based*, for instance, visual information about their distance from a target, can help them to find or track desired movements. Modeling how users control their movements may be beneficial when developing feedback strategies for improving motor learning.

Researchers have suggested that Linear Quadratic Gaussian (LQG) control may resemble how the central nervous system receives sensory information to estimate the body's current movement state and optimally controls the next movement action [1]. Using approaches similar to LQG, researchers have developed sensorimotor models like those explaining adaptive movement behavior [2] or redirected reaching [3]. However, while models like these consider implicit visual and proprioceptive feedback, they ignore the effects of explicit sensory feedback on movement learning. This work aims to predict how people learn movement tasks when given different sensory modalities of explicit error-based information. Here, we outline a sensorimotor model that showcases our initial effort to explain different movement behaviors when explicit error-based feedback is delivered through vision versus vibration.

To evaluate our model, we consider a 1 Degree of Freedom (DoF) handle sliding task where the goal position is initially unknown. We ask participants to learn the goal position with either error-based vision or vibration feedback using a physical system. We then simulate the results with our model by accounting for the differing uncertainties in the two sensory modalities. Our results are a step towards predicting how different explicit sensory feedback might affect a person's motor adaptation performance and learning.

II. Modeling Sensory Assistance

We developed a sensorimotor model (Fig. 1) based on our 1 DoF sliding task. We evaluate whether changing the level of uncertainty associated with our observation of explicit positional error–provided through visual or vibration feedback–results in changes in movement trajectories. To match our pilot study task, our model starts with an initial guess of the goal, which is updated throughout the simulation.

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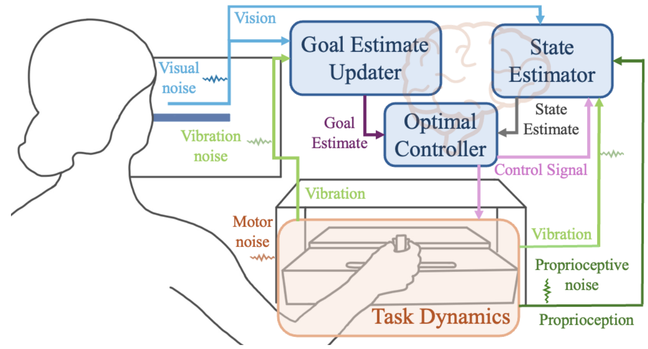

Fig. 1. Outline of our sensorimotor model in relation to the study task.

Dynamics: We model the hand-handle system as a linear mass-damper ($m = 1$ kg, $b = 10$ Ns/m) driven by the user's force, $u(t)$, imparted on the system (Equation 1).

$$\dot{p}(t) = v(t) \qquad m\dot{v}(t) = u(t) - bv(t) \tag{1}$$

For our problem, we consider the system state vector $\mathbf{x}(t) = [p(t) \;\; v(t) \;\; e(t)]^T$ in the horizontal direction. The error between the current position and the goal position, $e(t) \triangleq p_{goal} - p(t)$, captures the explicit error information given to the user through either visual or vibration feedback during the sliding task. The error signal changes as follows: $\dot{e}(t) = -v(t)$. Motor noise (Gaussian noise: $\mu = 0$, $\sigma = 0.1$ mm) is added to account for motor variability.

Observations: We assume that users observe each variable in the state vector through noisy proprioceptive, tactile, or visual sensory signals. Given our pilot study setup, proprioceptive noise is added to the observations of position and velocity, while either visual or vibration noise (Gaussian noise: $\mu = 0$, $\sigma_{visual} = 0.5$ mm or $\sigma_{vibration} = 5$ mm), is added to the observation of positional error. We assume that vibration noise has a larger variance than visual noise. This noise accounts for the resulting differences in the visual versus vibration conditions simulated.

Goal Estimate Updates: As people gain information about the environment, they update their beliefs about the goal position (initially unknown). During the trial, when the error changes signs, we update $p_{goal} = p_{obs} + e_{obs}$ where p_{obs} and e_{obs} are the position and error observations, respectively. We based this heuristic on instructions from the pilot study.

State Estimates: People use their noisy sensory observations and internal environment model to estimate their state during movements. This process is captured through a Kalman filter in our model.

Optimal Movement Control: Using the estimates of position and velocity at each time step, we use a linear quadratic

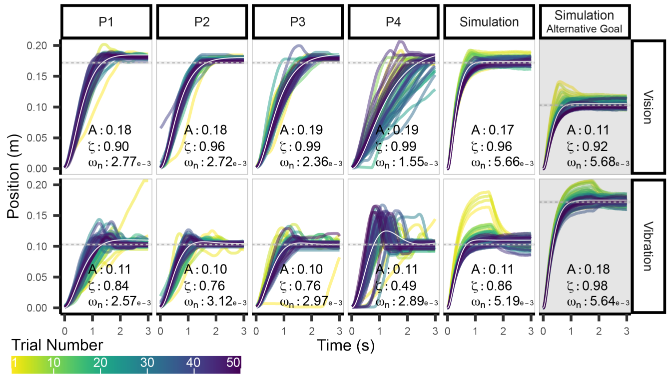

Fig. 2. Participant and model trajectories in vision and vibration feedback conditions. Colors mark trials; the goal is dashed gray, and the average underdamped fit is white. Average A, ζ, and ω_n are reported. Plots with a gray overlay show simulated trajectories with alternative goal positions.

regulator (LQR) to determine the next motor command, corresponding to the force applied by the user onto the handle. Here we chose the state cost Q and control cost R values based upon qualitative observation of the pilot data.

Between Trial Updates: To model learning between trials, we initialize the goal estimate of each trial as the last goal estimate of the previous trial plus some uncertainty (Gaussian noise: $\mu = 0$, $\sigma_{initial} = 5$ cm). This uncertainty is decreased between trials to explain memory and learning effects.

III. Pilot Study Design

We ran a within-subjects pilot study with 4 participants (IRB#34826) to validate our model with two explicit error-based sensory conditions: visual and vibrotactile. In each trial, participants moved a 1 DoF haptic device [4], trying to reach the goal in 2 seconds and receiving either visual feedback via Processing (https://processing.org/) or vibration feedback directly through the device's handle. The explicit sensory feedback provided participants with information about their error relative to the goal, where the minimum perceived vibration intensity (vibration condition) or line length on the screen (vision condition) corresponded to the goal. The goal location was different in each condition, but the same across those trials. Participants completed 50 trials per condition. Before the conditions, participants were trained to ensure they understood the task and timing. Participants completed the study in less than an hour.

IV. Preliminary Results

Four right-handed participants (2 ♀, 2 ♂, age μ = 23) were recruited and compensated for completing the pilot study.

We fit each resulting trial trajectory to an underdamped step response model. The output parameters, A (amplitude), ζ (damping ratio), and ω_n (natural frequency), were analyzed with linear mixed-effects models (*lmerTest*) in R, with *condition* as a fixed effect and random intercepts for participants. For the pilot study data, a multivariate test with the three-parameter vector was significant (Pillai = 0.92, F(3, 396) = 1615, $p < 0.001$). Additional univariate models with Holm-adjusted p-values (all $p < 0.001$) indicated: A decreased by 0.08 (due to the goal position decrease), ζ decreased 0.25, and ω_n increased by $5.4\text{e}{-4}$ rad/s. Note that P4 demonstrates the largest of these changes (Fig. 2).

Thus, moving from vision to vibration information for error resulted in less damped movements that unfolded more quickly, indicating a transition to a faster but less stable control regime. Our pilot results are consistent with previous observations between vibration and visual feedback [5]. We ran a similar analysis on the model-based data without any random intercepts for participants. We found similar results between *conditions* with our model (Pillai = 0.97, F(3, 96) = 1008, $p < 0.001$). Furthermore, the univariate results indicated a 0.06 decrease in A ($p < 0.001$), 0.1 decrease in ζ ($p = 0.0014$), and a $4.7\text{e}{-4}$ decrease in ω_n ($p < 0.001$).

V. Discussion & Future Work

The simulation versus participant results show different trends for the natural frequency ω_n of the fit trajectories from vision to vibration, but the same trend for the damping ratio ζ (the amplitude A depended on the differing goals). Simulations under alternative goal positions predict resulting trajectories with vision to vibration trends different from the original simulation. The results suggest that differences in sensory noise between the vision and vibration conditions, as modeled, account for *some* of the difference in the resulting trajectories; however, goal position likely contributes. This model serves as a first step toward developing ways to understand the effects of explicit sensory feedback on movement.

Future work should consider limitations to the model and study design. Revisions of the model should expand to multi-dimensional movements. Additionally, cost functions should be fit to each participant to better predict how different feedback will impact individual movement policies. Future iterations of the study will include more participants and will vary the goal positions across participants to determine whether the observed differences in movement trajectories come from the choice of goal position alone.

Haptic feedback design is often a manual process, requiring expert creation, hand tuning, iteration, and selection of a haptic signal from a large design space. The long-term goal of this work is to simulate the effects of different types of feedback on motor adaptation tasks–providing a valuable tool for haptic designers to choose *optimal* feedback.

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