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RESEARCH ARTICLE

Control of Movement

Visual accuracy dominates over haptic speed for state estimation of a partner during collaborative sensorimotor interactions

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Abstract

We routinely have physical interactions with others, whether it be handing someone a glass of water or jointly moving a heavy object together. These sensorimotor interactions between humans typically rely on visual feedback and haptic feedback. Recent single-participant studies have highlighted that the unique noise and time delays of each sense must be considered to estimate the state, such as the position and velocity, of one's own movement. However, we know little about how visual feedback and haptic feedback are used to estimate the state of another person. Here, we tested how humans utilize visual feedback and haptic feedback to estimate the state of their partner during a collaborative sensorimotor task. Across two experiments, we show that visual feedback dominated haptic feedback during collaboration. Specifically, we found that visual feedback led to comparatively lower task-relevant movement variability, smoother collaborative movements, and faster trial completion times. We also developed an optimal feedback controller that considered the noise and time delays of both visual feedback and haptic feedback to estimate the state of a partner. This model was able to capture both lower task-relevant movement variability and smoother collaborative movements. Taken together, our empirical and modeling results support the idea that visual accuracy is more important than haptic speed to perform state estimation of a partner during collaboration.

NEW & NOTEWORTHY Physical collaboration between two or more individuals involves both visual and haptic feedback. Here, we investigated how visual and haptic feedback is used to estimate the movements of a partner during a collaboration task. Our experimental and computational modeling results parsimoniously support the notion that greater visual accuracy is more important than faster yet noisier haptic feedback when estimating the state of a partner.

collaboration; human-human interaction; optimal feedback control; sensorimotor; uncontrolled manifold

INTRODUCTION

Collaborative sensorimotor interactions are ubiquitous in our daily lives, from shaking hands, dancing with a partner, to a physical therapist interacting with a patient. Visual and haptic feedback of another person mediates these sensorimotor interactions between humans (1–4). How the sensorimotor system accounts for the noise and time delays of visual feedback and haptic feedback has been well investigated during tasks that involve a single human (5–9). During sensorimotor interactions with two or more people, others have recognized that visual and haptic feedback influences performance (10–13). Yet, we know relatively little about how visual feedback and haptic feedback, each with their own unique sensory noise and time delays, are used to estimate the state (e.g., position and velocity) of another person. State

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estimation of a partner is likely important for the successful coordination of actions between humans. A better understanding of sensorimotor interactions between humans can be used to inform the development of physically guided rehabilitation by another human (14, 15) or robot (16, 17), as well as developing collaborative robots that interact more seamlessly with humans (4, 18, 19).

Optimal feedback control has been a powerful framework to capture human movement behavior (20, 21). Only recently has this framework been used to examine how multiple humans jointly coordinate their actions during collaborative tasks. Takagi et al. (11, 12) had humans perform a tracking task individually or with a partner(s). When acting alone, individuals attempted to place their cursor within a moving target. When acting with one or more partners, each person attempted to place their cursor within a common moving target when their hands were interconnected by a virtual spring. Performance was measured as the difference between a cursor and the target over a trial. They found individuals displayed improved performance when they were connected to another person compared with to when they did the task alone. In line with an optimal feedback control model, they suggested that joint performance improved because individuals were using haptic feedback to estimate the goals of their partner. Subsequent empirical and modeling work found that visual feedback and haptic feedback, compared with haptic feedback alone, improved joint performance during a collaborative reaching task (13, 22). Yet to date, optimal feedback control models of sensorimotor interactions between humans have not accounted for the unique noise and time delays of different senses.

Visual feedback and haptic feedback have varying amounts of sensory noise and time delays. Seminal work by Ernst and Banks (8) showed that the nervous system weighs visual and haptic feedback according to their respective sensory acuities to perform state estimation in a statistically optimal fashion. Specifically, they and others found that visual feedback is more heavily weighted since it has less sensory noise than haptic feedback (8, 23–25). These works examined state estimation using perceptual tasks where sensory time delays were not important. However, muscular responses to stimulus sensed by proprioception and vision can respectively be delayed by ∼50 ms and 100 ms (7, 9, 26). During movement, the sensorimotor system must consider the unique time delay of each sensory modality to perform state estimation (9, 26). Crevecoeur et al. (9) and Kasuga et al. (26) examined the influence of visual feedback and proprioceptive feedback time delays when participants reached to a target. They found that the sensorimotor system weighs proprioceptive feedback more than visual feedback, since proprioceptive feedback has shorter time delays despite more noise. They also showed when individuals used both visual and proprioceptive feedback they had less movement variability compared with using only proprioceptive feedback. These findings were predicted by an optimal feedback control model with a state estimator (i.e., Kalman filter) that considered both sensory noise and time delays of multiple senses. Work on sensorimotor interactions between multiple humans has suggested that haptic feedback and visual feedback are used for state estimation of a partner (2, 3, 12, 13). Similar to past work (27), we refer to haptic feedback as the sense of touch that is used to estimate the state of a partner. It is well established that mechanoreceptors involved with touch and proprioception have relatively shorter time delays and more sensory noise than vision (8, 28, 29). Currently, it is unclear how sensory noise and time delays that are unique to visual feedback and haptic feedback influence the state estimation of a partner.

We conducted two experiments to test how humans rely on visual feedback and/or haptic feedback during a collaborative reaching task. We tested the idea that sensory noise and time delays of visual feedback and haptic feedback influence the state estimation of a partner. For both experiments, a human pair jointly controlled the midpoint between their hands. Participants attempted to move the jointly controlled midpoint to a virtually displayed target. In *experiment 1*, we constrained reaching movements and the position of the target along a single, lateral dimension. In *experiment 2*, participants could move their hands along the forward and lateral dimensions when reaching forward to the virtually displayed target. In trials with visual feedback, participants saw the position of their partner on the screen via a cursor. In trials with haptic feedback, participants could feel the movement of their partner via a virtual spring that was linked between the human pair. In a two-way repeated-measures design, participants received either: *1*) NoVision-NoHaptic (no visual feedback, no haptic feedback), *2*) NoVision-Haptic (no visual feedback, haptic feedback), *3*) Vision-NoHaptic (visual feedback, no haptic feedback), and *4*) Vision-Haptic (visual feedback, haptic feedback) of their partner. If higher visual accuracy (i.e., low noise) is more important than a shorter haptic time delay for state estimation of a partner, we would expect less movement variability of the jointly controlled midpoint (i.e., task-relevant movement variability) in conditions involving visual feedback relative to conditions involving haptic feedback. Conversely, if a shorter haptic time delay is more important than higher visual accuracy (i.e., low noise) for state estimation of a partner, we would expect less task-relevant movement variability of the jointly controlled midpoint in conditions involving haptic feedback relative to conditions involving visual feedback. Finally, we developed an optimal feedback control model, with a state estimator that considered sensory noise and time delays of visual and haptic feedback, to capture the empirical results of both experiments.

METHODS

Participants

Eighty individuals participated across two experiments: 40 individuals (20 human pairs; age 18–30 yr) participated in *experiment 1*, and 40 individuals (20 human pairs; age 18–30 yr) participated in *experiment 2*. All participants provided written informed consent to participate in the experiment and the procedures were approved by the University of Delaware's Institutional Review Board (*experiment 1*) and McMaster University's Research Ethics Board (*experiment 2*). All participants reported that they were free from musculoskeletal injuries, neurological or sensory impairments. Furthermore, all participants had a normal or corrected vision. Across the two experiments, two participants were left-hand dominant and the rest were right-hand dominant. In addition to a base compensation of $5.00, we informed the participants that they would receive a performance-based compensation of up to $5.00. Participants received the full $10.00 once they completed the experiment, irrespective of their performance.

Apparatus

For both experiments, we used two end point KINARM robots (Fig. 1*A*; BKIN Technologies, Kingston, ON) that can interact with each other in real-time. Each participant of a human pair was seated on an adjustable chair in front of one of the end-point robots. Each participant grasped the handle

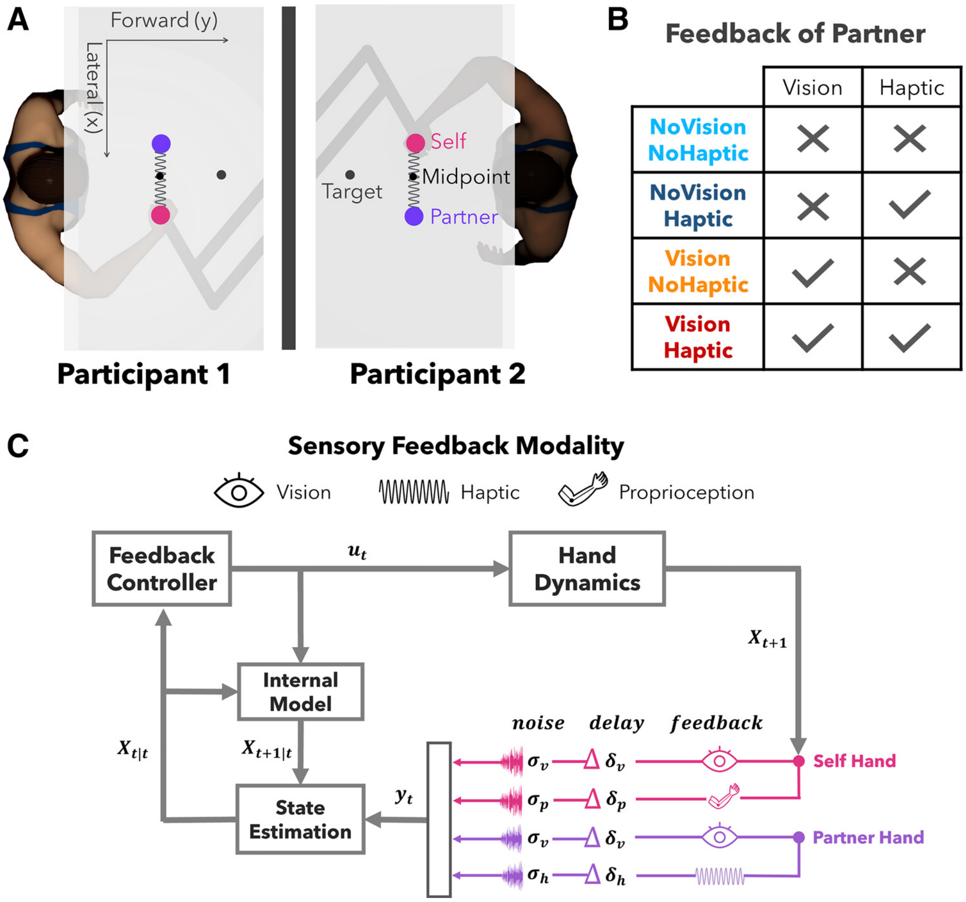

Figure 1. *A*: general experimental task for *experiments 1* and *2*. Human pairs performed a collaborative reaching task. For each trial, both participants stabilized their hands within their own start position. Following a short and random delay, their start position became a cursor that was aligned with their hand position (pink, "self") and a circular target appeared on the screen. The midpoint was the average hand position of the human pair. Both participants were instructed to move the midpoint to the target. The target color changed to blue when the midpoint was within the target. To increase the reliance on using sensory information of a partner, the midpoint was not displayed to the participants. A trial was complete once the midpoint was within the target for 1 s. In both experiments, participants received the message, "Good," "Too slow," or "Too fast" if they completed the trial between 2.1 and 2.5 s, >2.5 s, or <2.1 s to complete the trial, respectively. *Experiment 1* was a one-dimensional reaching task, where the target was placed to the left or right of the midpoint. Here, each participant's hand was constrained to move along the lateral direction. *Experiment 2* was a two-dimensional reaching task, where the target was forward of the start position and the hands were free to move anywhere along the forward and lateral directions. *B*: visual and haptic feedback. Participants always received visual feedback of their own hand position (pink cursor). Each participant relied on haptic and/or visual feedback of their partner to estimate the location of the midpoint. We manipulated the presence of visual feedback by either displaying or not displaying a purple cursor that represented their partner's hand position. We manipulated the presence of haptic feedback by either enabling or disabling a virtual spring between the hands of the participants. Human pairs performed the task under one of the four conditions: *1*) NoVision-NoHaptic [no visual feedback, no haptic feedback], *2*) NoVision-Haptic [no visual feedback, haptic feedback] *3*) Vision-NoHaptic [visual feedback, no haptic feedback], and *4*) Vision-Haptic [visual feedback, haptic feedback]. *C*: optimal control model schematic. Each participant of a human pair was simultaneously modeled as an optimal feedback controller. By considering both optimal feedback controllers simultaneously, we were able to capture human-human sensorimotor interactions. Here, we represent the optimal feedback controller of a single participant that utilizes state estimation of a partner's hand position and velocity through visual and/or haptic feedback. The feedback controller generates a control signal (u_t) based on a current state estimate ($X_{t|t}$) of the hand and jointly controlled midpoint. The control signal can be thought to represent muscle activity that is subsequently used to generate forces that move the hand. An efference copy of the control signal is passed through an internal model, a representation of the dynamics, which produces a prediction of the future state ($X_{t+1|t}$). The controller observed its own hand states (X_{t+1}) through vision and proprioception. Depending on the experimental condition, each controller observes the state of the partner's hand through visual (v) and/or haptic (h) feedback. Haptic feedback was enabled by accounting for the dynamics of the virtual spring. Each source of sensory feedback was modeled with an appropriate level of noise (σ) and delay (δ). An optimal state estimator utilizes the prior prediction from the internal model and state observation (y_t) of the hand and partner to produce the posterior state estimates of the system, including the jointly controlled midpoint.

of a robotic manipulandum and made reaching movements in the horizontal plane. A semi-silvered mirror blocked the vision of the upper limb and displayed virtual images (e.g., targets, cursors) from an LCD screen. The semi-silvered mirror occluded the vision of their hand. Kinematic data were recorded at 1,000 Hz and stored offline for data analysis.

General Experimental Design

We designed two experiments where participants had to rely on visual or haptic feedback from their partner during collaborative reaching tasks. Human pairs collaborated by jointly controlling the midpoint between their hands (Fig. 1*A*). To begin the task, each participant stabilized their dominant hand within a pink circle (1 cm diameter) shown on the screen. After a short and random delay (uniform distribution: 1.0–1.5 s), this pink circle became a cursor that was aligned with their hand position for the rest of the trial. Simultaneously, a white circular target was displayed on the screen. The size and location of the target was different in *experiment 1* and *experiment 2* (see *Experiment 1 Design* and *Experiment 2 Design*). At the start of the reach, the distance between the two participants' hands was 10 cm. We instructed human pairs to move the midpoint between their hands to the target. To increase the need to rely on the movement feedback of their partner, participants did not receive visual feedback of the midpoint during the experimental trials. The target color changed to blue when the midpoint was within the target. A trial was complete once the midpoint was within the target for 1 s. Participants received a message saying "Good" when they completed the trial between 2.1 s and 2.5 s. They received a message saying "Too slow" or "Too fast" if they respectively took more than 2.5 s or less than 2.1 s to complete the trial.

The goal of both experiments was to test how humans rely on visual feedback and/or haptic feedback of a partner when performing a collaborative reaching task. We manipulated the presence of visual feedback by either displaying or not displaying a purple cursor (1 cm diameter) that represented the position of their partner's hand. Participants always saw their own cursor as a pink circle. As in past work (10–13, 30–32), we manipulated the presence of haptic feedback by either enabling or disabling a virtual spring. Each end of the virtual spring was aligned to the hand of a participant (Fig. 1*A*). Thus, the length of the virtual spring was always the same as the distance between the hands of the two participants. Participants did not see an image of the virtual spring. Experiment-specific spring constants are reported in *Experiment 1 Design* and *Experiment 2 Design*. Human pairs performed four conditions in a two-way repeated-measures experimental design: *1*) NoVision-NoHaptic (no visual feedback, no haptic feedback), *2*) NoVision-Haptic (no visual feedback, haptic feedback), *3*) Vision-NoHaptic (visual feedback, no haptic feedback), and *4*) Vision-Haptic (visual feedback, haptic feedback) (Fig. 1*B*).

Human pairs performed task familiarization, partner feedback familiarization, and experimental trials with interleaved perturbation trials. First, human pairs performed six task familiarization trials to become familiar with the task goals. Here, they received combined visual-haptic feedback of their partner. Furthermore, and only during task familiarization, human pairs also received visual feedback of the midpoint (red circle, 0.5 cm diameter). This allowed participants to understand that the goal of the task was to move the midpoint to the target. Here they were not provided feedback on trial completion time. Human pairs then performed 40 partner feedback familiarization trials to become familiar with the four different types of partner feedback: NoVision-NoHaptic, NoVision-Haptic, Vision-NoHaptic, and Vision-Haptic. They performed 10 trials for each of these four types of partner feedback. The type of partner feedback was randomized for each trial. They were also given feedback on trial completion time to become familiar with timing requirements of the task. Experimental and perturbation trials for each experiment are described in *Experiment 1 Design* and *Experiment 2 Design*.

Experiment 1 Design

The goal of the first experiment was to study participant movement behavior with different forms of sensory feedback about their partner's movements. We constrained the task to a single dimension in *experiment 1*. Here, we restricted each participant's hand movements to the lateral dimension using a virtual force channel (stiffness = 100 N/m). The white circular target (diameter 0.5 cm) was displayed either 15 cm to the left or right relative to the initial position of the midpoint. When providing haptic feedback, we enabled a virtual spring (k = 50 N/m, resting length = 10 cm).

Following the six task familiarization trials and 40 partner feedback familiarization trials (described earlier), participants completed 256 experimental trials and 64 mechanical perturbation trials. They performed 80 trials separately for each condition: *1*) NoVision-NoHaptic, *2*) NoVision-Haptic *3*) Vision-NoHaptic, and *4*) Vision-Haptic. Of the 80 trials in each block, there were 64 experimental trials and 16 mechanical perturbation trials. The goal of the mechanical perturbations was to further challenge the participants while completing the task. For the perturbation trials, eight pushed the hand further to the right when participants were reaching toward a right target. Similarly, eight trials pushed the hand further to the left when participants were reaching toward a left target. We randomized the order of the 80 trials within each condition. Condition order was randomized.

To apply mechanical perturbations, a Gaussian-shaped perturbation force (peak magnitude = 40 N, standard deviation = 25 ms) was applied to each participant's hand. The force was applied to both participants when the midpoint was located 2 cm away from the target.

Experiment 2 Design

The goal of the second experiment was to replicate the results of the first experiment when generalizing to a two-dimensional collaborative reaching task. Here, human pairs could move their hands and the midpoint in both the forward and lateral directions. The white circular target (diameter = 0.8 cm) was displayed 15 cm forward relative to the initial position of the midpoint. Based on piloting, we increased the diameter of the target to 0.8 cm so that the participants could complete the task within approximately the same amount of time as *experiment 1*. In the first experiment, we found that task performance was not improved when human pairs used haptic feedback compared with no feedback. To enhance the potential to utilize haptic feedback, in *experiment 2* we doubled the stiffness of the virtual spring (k = 100 N/m, resting length = 10 cm).

Following the six task familiarization trials and 40 partner feedback familiarization trials (described earlier), participants completed 256 experimental trials, 64 mechanical perturbation trials, and 64 visual perturbation trials. They performed 96 trials separately for each condition: *1*) NoVision-NoHaptic, *2*) NoVision-Haptic *3*) Vision-NoHaptic, and *4*) Vision-Haptic. Similar to *experiment 1* we again used mechanical perturbation trials to challenge participants during the task. A potential limitation of these mechanical perturbations is that they may lead to different displacements between individuals given their unique limb impedance properties (i.e., stiffness, inertia), which would likely challenge each participant differently. Thus, in *experiment 2* we also used visual perturbations to equally displace the cursor position by 5 cm in the same direction for each participant. During visual perturbation trials, both participants' cursors were visually jumped by the same lateral distance and along the same direction (right or left). The nondisplayed midpoint also shifted such that it remained between the hand cursors. Participants were still required to move the midpoint to the target. Of the 96 trials in each block, there were 64 experimental trials, 16 mechanical perturbation trials, and 16 visual perturbation trials. Of the 16 mechanical or visual perturbation trials, 8 trials were perturbed leftward and the remaining 8 trials were perturbed rightward. We randomized the order of the 96 trials within each condition. Condition order was randomized.

To apply mechanical perturbations, a Gaussian-shaped perturbation force (peak magnitude = 40 N, standard deviation = 25 ms) was applied to each participant's hand. The force was applied to both participants when the midpoint moved 2 cm forward relative to its start position. To apply visual perturbations, each participant's blue cursor was laterally jumped by 5 cm. The cursors were jumped once the midpoint moved 2 cm forward relative to its start position.

Data Analysis

We analyzed the results from experimental trials. All kinematic data were filtered with a 6th-order, low-pass Butterworth filter with a 15-Hz cutoff frequency (33).

Task-relevant and task-irrelevant movement variability.

Past work has used movement variability as a metric of state estimation during individual reaching movements (9, 26). Here, we build upon this approach to examine state estimation of a partner during a collaborative reaching task. Specifically, we examined whether visual feedback or haptic feedback of a partner influenced task-relevant movement variability.

Both the minimum intervention principle and uncontrolled manifold hypothesis suggest that the sensorimotor system controls movements that impact performance (task-relevant), but allows movements to remain uncontrolled when they do not impact task performance (task-irrelevant). The result of this control strategy is less variability along task-relevant dimensions of the task and greater variability along task-redundant dimensions of the task (34, 35). This observation in the literature is predicted by optimal feedback control since it is energetically costly to correct for task-irrelevant movements that do not impact task performance (20).

Since two participants jointly controlled the midpoint between their hands, we could decompose the hand variability of participants across the trials into task-relevant and task-irrelevant dimensions. In our task, task-relevant movements are hand position changes that influence the position of the midpoint. Conversely, task-irrelevant movements are hand position changes that do not influence the position of the midpoint. As an example of task-redundant movements, if both participants moved their hands at equal distances in opposite directions there would be no position change of the midpoint.

We used uncontrolled manifold analysis to decompose the hand variability of the two participants into task-relevant and task-irrelevant dimensions (36). The mapping between the hand coordinates and the midpoint is shown in *Eqs. 1* and *2*,

$$C = \begin{bmatrix} x_m \\ y_m \end{bmatrix} = Ah, \tag{1}$$

$$A = \begin{bmatrix} 0.5 & 0.5 & 0 & 0 \\ 0 & 0 & 0.5 & 0.5 \end{bmatrix}, \; h = \begin{bmatrix} x_l & x_r & y_l & y_r \end{bmatrix}^T, \tag{2}$$

where x_m, y_m are midpoint coordinates, x_l, y_l are left-hand coordinates, x_r, y_r are right-hand coordinates, and A is the transformation matrix from the hand coordinates to the midpoint coordinates.

For each time point, we placed the hand coordinate vectors (h_1, h_2, …, h_n) from all trials (n trials) into a matrix H (*Eq. 3*). We then subtracted the mean hand coordinate vector (h_{mean}) from H to obtain hand coordinate deviations, H_d (*Eq. 4*).

$$H = \begin{bmatrix} h_1 & h_2 & \dots & h_n \end{bmatrix} \tag{3}$$

$$H_d = H - h_{mean} \tag{4}$$

We projected the hand deviations onto the null space vectors (v_i) of the transformation matrix A,

$$H_{dnull} = \sum_{i=1}^{2} (v_i^T . H_d) v_i \tag{5}$$

Using the null space-projected hand deviations, we obtained the projection of the hand deviations onto the task space,

$$H_{dtask} = H_d - H_{dnull}. \tag{6}$$

We then computed the task-relevant (task space) and task-irrelevant (null space) movement variabilities,

$$\text{Task-Relevant Movement Variability} = \frac{\sum_{j=1}^{4} \sum_{k=1}^{n} (H_{dtask})_{jk}^2}{n}, \tag{7}$$

$$\text{Task-Irrelevant Movement Variability} = \frac{\sum_{j=1}^{4} \sum_{k=1}^{n} (H_{dnull})_{jk}^2}{n}. \tag{8}$$

For the summary box plots, we averaged the task-relevant and task-irrelevant movement variability between 2.1 and 2.5 s, which aligned with the instructed trial time.

Trial completion time.

For each trial, we measured the time from the start of the trial (target displayed) until the midpoint was stabilized at the target for 1 s.

Movement smoothness.

Smooth movements are indicative of well-trained sensorimotor behavior and good spatiotemporal coordination (37, 38). We used log dimensionless jerk (39) to quantify the movement smoothness of the midpoint.

$$\text{Midpoint jerk} = -\ln\left(\frac{(t_{\mathrm{f}} - t_{\mathrm{i}})^3}{|v_{\max}|^2}\int_{t_{\mathrm{i}}}^{t_{\mathrm{f}}} |\ddot{v}|^2 \mathrm{d}t\right), \tag{9}$$

where v is the velocity of the midpoint, t_{i} is the trial start time, and t_{f} is the trial end time.

Optimal Feedback Control Model

We used optimal feedback control to predict movement behavior of human pairs. This general framework has been used to model sensorimotor behavior in individual human tasks (7, 20) and paired human tasks (31). We modeled each participant controlling their hand as a separate optimal feedback controller (13). Together, these two optimal feedback controllers moved the midpoint toward the desired target. Crucially, to capture differences between experimental conditions, the optimal feedback controllers relied on visual and/or haptic feedback of both self and the interacting partner.

System dynamics.

As mentioned earlier, each hand was modeled as a point mass. The continuous-time dynamics of the point mass representing the left participant's hand were as follows:

$$m\dot{p}_{\mathrm{l}}^x = -k\left(1 - \frac{s}{\left((p_{\mathrm{l}}^x - p_{\mathrm{r}}^x)^2 + (p_{\mathrm{l}}^y - p_{\mathrm{r}}^y)^2\right)^{1/2}}\right)(p_{\mathrm{l}}^x - p_{\mathrm{r}}^x)$$

$$-cv_{\mathrm{l}}^x + f_{\mathrm{l}}^x, \tag{10}$$

$$m\dot{p}_{\mathrm{l}}^y = -k\left(1 - \frac{s}{\left((p_{\mathrm{l}}^x - p_{\mathrm{r}}^x)^2 + (p_{\mathrm{l}}^y - p_{\mathrm{r}}^y)^2\right)^{1/2}}\right)(p_{\mathrm{l}}^y - p_{\mathrm{r}}^y)$$

$$-cv_{\mathrm{l}}^y + f_{\mathrm{l}}^y, \tag{11}$$

$$\tau\dot{f}_{\mathrm{l}}^x = g_{\mathrm{l}}^x - f_{\mathrm{l}}^x, \quad \tau\dot{g}_{\mathrm{l}}^x = u_{\mathrm{l}}^x - g_{\mathrm{l}}^x, \tag{12}$$

$$\tau\dot{f}_{\mathrm{l}}^y = g_{\mathrm{l}}^y - f_{\mathrm{l}}^y, \quad \tau\dot{g}_{\mathrm{l}}^y = u_{\mathrm{l}}^y - g_{\mathrm{l}}^y, \tag{13}$$

where x and y superscripts correspond respectively to the lateral and forward dimensions. The subscripts l and r correspond respectively to the two controllers representing the left hand and the right hand. p represents position, v is velocity, f represents internally generated muscle forces that move the hand (e.g., by muscle), and u is the control signal. m = 1 kg is the mass of the hand, τ = 40 ms represents the time constant of the second-order low-pass filter that approximates the relationship between muscle activity (u) and the internally generated muscle force (40), which are linked with an intermediate variable (g). c = 0.15 Ns/m is a damping constant that collectively models the damping properties of joints and muscles. k = 10 N/m is the spring constant and s = 0.1 m is the resting length of the spring connected between the two hands of the spring connected between the two participants. We set k to zero to simulate experimental conditions where haptic feedback of the partner was disabled. The state dynamics of the right hand were defined with a similar set of equations.

A central assumption of our computational approach was that two optimal feedback controllers, each representing one person, interact to move the midpoint. The dynamics of the midpoint is as follows:

$$\dot{p}_{\mathrm{m}}^x = \frac{v_{\mathrm{l}}^x + v_{\mathrm{r}}^x}{2}, \tag{14}$$

$$\dot{p}_{\mathrm{m}}^y = \frac{v_{\mathrm{l}}^y + v_{\mathrm{r}}^y}{2}. \tag{15}$$

Each controller considers all of its own states, the position and velocity of the midpoint, and the position and velocity of their partner's hand. The states considered by the left-hand participant were defined as follows

$$x_t = [p_{\mathrm{m}}^x \, p_{\mathrm{m}}^y \, X_{\mathrm{l}} \, X_{\mathrm{r}} \, p_{\mathrm{target}}^x \, p_{\mathrm{target}}^y]^T, \tag{16}$$

where p_{m}^x and p_{m}^y are the position coordinates of the midpoint, p_{target}^x and p_{target}^y are the position coordinates of the target. X_{l} represents its own states and X_{r} represents their partner's (right-hand participant) states, which are expanded as follows:

$$X_{\mathrm{l}} = [p_{\mathrm{lc}}^x \, v_{\mathrm{lc}}^x \, p_{\mathrm{l}}^x \, p_{\mathrm{l}}^y \, v_{\mathrm{l}}^x \, v_{\mathrm{l}}^y \, f_{\mathrm{l}}^x \, g_{\mathrm{l}}^x \, f_{\mathrm{l}}^y \, g_{\mathrm{l}}^y], \tag{17}$$

$$X_{\mathrm{r}} = [p_{\mathrm{rc}}^x \, v_{\mathrm{rc}}^x \, p_{\mathrm{r}}^x \, p_{\mathrm{r}}^y \, v_{\mathrm{r}}^x \, v_{\mathrm{r}}^y], \tag{18}$$

where, $p_{\mathrm{lc}}^x, p_{\mathrm{rc}}^x$ are the lateral cursor positions, $v_{\mathrm{lc}}^x, v_{\mathrm{rc}}^x$ are the lateral cursor velocities, p_{l}^x, p_{l}^y, p_{r}^x, p_{r}^y are the position coordinates of the hands, v_{l}^x, v_{l}^y, v_{r}^x, v_{r}^y are the velocity states of the hands, and f_{l}^x, f_{l}^y, g_{l}^x, g_{l}^y are the states of the second-order, low-pass filter. We maintained separate states for the cursor ($p_{\mathrm{lc}}^x, v_{\mathrm{lc}}^x, p_{\mathrm{rc}}^x, v_{\mathrm{rc}}^x$) and the hand ($p_{\mathrm{l}}^x, v_{\mathrm{l}}^x, p_{\mathrm{r}}^x, v_{\mathrm{r}}^x$) in the lateral dimension to accommodate lateral cursor jumps caused by visual perturbations. The state vector for the right-hand participant was designed in the same fashion (i.e., l become r, and r become l).

The system dynamics are nonlinear due to the spring linked between the hands. Hence, we linearized the system to design a locally optimal control law using an iterative Linear Quadratic Regulator (41). First, we applied Jacobian linearization to the continuous nonlinear dynamical system (*Eq. 16*) around a nominal trajectory u_t^*, x_t^*. We then transformed the continuous linearized system to a discrete linear system (*Eq. 17*) using Euler integration with a time step of Δt = 10 ms. The nonlinear dynamical model and the linearized system can be expressed as follows

$$x_{t+1} = f(x_t, u_t) + \varepsilon_t, \tag{19}$$

$$\delta x_{t+1} = A_t \delta x_t + B_t \delta u_t + \delta \varepsilon_t, \tag{20}$$

$$A_t = I + \Delta t \frac{\delta f_t}{\delta x_t},\ B_t = \Delta t \frac{\delta f_t}{\delta u_t}, \tag{21}$$

where $\delta x_t \in \mathbb{R}^{n_x}$ is the deviation of the state from a nominal trajectory x_t^*, and $\delta u_t \in \mathbb{R}^{n_u}$ is the deviation of control input from a nominal control sequence u_t^*. We obtained a nominal trajectory x_t^* by applying the nominal control sequence $u_t^* = 0$ to the nonlinear dynamical system using the fourth-order Runge–Kutta method. We assumed that the system is affected by additive noise $\varepsilon_t \in \mathbb{R}^{n_u}$, represented by a multidimensional Gaussian random variable with zero mean and covariance Ω^{ε}.

State feedback design.

To include state feedback delays, we augmented the state vector with previous states (*Eq. 20*). This allowed the observer to access delayed states, including delayed haptic feedback (Δh) and delayed visual feedback (Δv) according to:

$$\mathbf{x_t} = \begin{bmatrix} x_t & x_{t-1} & \dots & x_{t-\Delta h} & \dots & x_{t-\Delta v} \end{bmatrix}. \tag{22}$$

The observations made by the controller are

$$y_t = H\mathbf{x_t} + \omega_t, \tag{23}$$

where, $y_t \in \mathbb{R}^{n_y}$ is the vector of delayed state observations. Aligned with experiment conditions, the observation matrix H was designed to selectively observe the states delayed by haptic and/or visual feedback.

$$H = \begin{bmatrix} 0 & \dots & h_h & \dots & 0 \\ 0 & \dots & 0 & \dots & h_v \end{bmatrix}. \tag{24}$$

The controller observes the partner through visual feedback and haptic feedback. All forms of feedback were characterized using different feedback delays and sensory noise magnitudes. For haptic feedback of the partner, we assumed that the model could observe the difference in position and velocity states between the hands with a delay of 50 ms (42). For visual feedback from the partner, we assumed that the model could observe the position and velocity states of their partner's hand with a delay of 100 ms (7). We assumed that each controller observes its own states through proprioception and visual feedback with delays of 50 and 100 ms, respectively.

Sensory noise, $\omega_t \in \mathbb{R}^{n_y}$, is modeled using a multidimensional Gaussian random variable with zero mean and covariance Ω^{ω}. We set the standard deviations for the position (σ = 0.01 m), velocity (σ = 0.1 m/s), and force state (σ = 1 N) noise (43). This noise was scaled by partner haptic feedback (0.8), self-proprioceptive feedback (0.4), and partner and self-visual feedback (0.2) to capture the unique sensory noise associated with each form of feedback.

In accordance with the experiment, we did not allow the model to directly observe the position of the midpoint. The model estimated the position of the midpoint by observing the position and velocity states of itself and the partner. For the full matrix H, see Supplemental Material, Section A.

Since the system dynamics are nonlinear, we used an Extended Kalman Filter to estimate the state (44, 45). The posterior state estimate $\hat{x}_t$ is obtained online using a filter of the form (43):

$$\hat{x}_t = \hat{x}_{t|t-1} + K_t(y_t - H\hat{x}_{t|t-1}), \tag{25}$$

$$\hat{x}_{t|t-1} = f(\hat{x}_{t-1}, u_{t-1}), \tag{26}$$

where, $\hat{x}_{t|t-1}$ is the internal prior prediction of the state given the previous state estimate $\hat{x}_{t-1}$ and the efference copy u_{t-1}. A central assumption here is that our sensorimotor system obtains a prior prediction of the state using an accurate internal model of the state dynamics (*Eq. 16*). The prior prediction of the states is then updated using sensory measurements to obtain a posterior state estimate. The sequence of Kalman filter gains K_t were calculated recursively (Supplemental Material, Section A).

Control design.

The goal of the controller is to move the state of the system from an initial state (x_1) to a target state (x_{target}) in n time steps by minimizing the total linearized quadratic cost J_1,

$$J_1 = \frac{1}{2}(x_n + \delta x_n)^T Q_n (x_n + \delta x_n) + \frac{1}{2}\sum_{t=1}^{n-1}(x_t + \delta x_t)^T Q (x_t + \delta x_t) + (u_t + \delta u_t)^T R (u_t + \delta u_t). \tag{27}$$

The quadratic cost penalizes large control signals and deviation from the target state at the final step. The quadratic cost matrices Q_n, Q, and R are fully described in Supplemental Material, Section A. The state-feedback controller for the aforementioned control problem is as follows (41):

$$\delta u_t = -L_t \delta \hat{x}_t - L_t^v v_{t+1} - L_t^u u_t^*, \tag{28}$$

where, $\delta \hat{x}_t = \hat{x}_t - x_t$ is an unbiased estimate of the state deviation. The state estimate $\hat{x}_t$ is updated recursively (*Eqs. 25* and *26*) using an Extended Kalman Filter. The feedback gains L_t, L_t^v, and L_t^u were obtained by backward recursion before the trial simulation (Supplemental Material, Section A).

Model predictions.

We simulated three partner feedback conditions from the experiment *1*) NoVision-Haptic, *2*) Vision-NoHaptic, and *3*) Vision-Haptic. Note that we did not model the NoVision-NoHaptic condition that would rely solely on feedforward control because our optimal feedback controllers rely on state feedback of the partner to estimate the location of the midpoint. Similar to Kasuga et al. (26), we simulated 100 human pairs each performing 64 trials per condition to predict task-relevant and task-irrelevant movement variability for the three feedback conditions mentioned earlier. To generate summary box plots, we averaged task-relevant and task-irrelevant movement variability across the simulated human pairs. To predict movement smoothness, we calculated midpoint jerk for each trial as described in *Data Analysis*.

Statistical Analysis

We used analysis of variance (ANOVA) as omnibus tests to determine whether there were main effects and interactions. For both experiments, we used a 2 (No Vision or Vision) × 2 (No Haptic or Haptic) repeated-measures ANOVA for each dependent variable. We followed up the omnibus tests with mean comparisons using nonparametric bootstrap hypothesis tests (n = 1,000,000) (46, 47). Mean comparisons were Holm–Bonferroni corrected to account for multiple comparisons. We computed the common language effect sizes ($\hat{\theta}$) for all mean comparisons (48). We performed Grubb's test to detect outliers. The statistical results and interpretation remained the same with or without the outliers, so for brevity, we only present the results that included all individuals. Significance threshold was set at α = 0.5.

RESULTS

We conducted two experiments to test how humans rely on visual feedback and/or haptic feedback of their partner to complete a collaborative reaching task (Fig. 1). Specifically, we tested the idea that the unique sensory noise and time delays of visual feedback and haptic feedback influence state estimation of a partner. Each human pair performed four partner feedback conditions: *1*) NoVision-NoHaptic (no visual feedback, no haptic feedback), *2*) NoVision-Haptic (no visual feedback, haptic feedback), *3*) Vision-NoHaptic (visual feedback, no visual feedback), and *4*) Vision-Haptic (visual feedback, haptic feedback).

Experiment 1

In *experiment 1*, participant hand movements were restricted along the lateral dimension. The target was displayed either on the left side or the right side of the initial position of the midpoint.

Individual and group movement behavior of human pairs.

Individual participant hand trajectories and midpoint trajectories from an exemplar human pair are shown for the experimental trials of each feedback condition (Fig. 2*A*). This human pair worked in unison to efficiently move the midpoint to the displayed target location. For all conditions, their lateral hand position variability was greater than the lateral midpoint position variability. This human pair displayed lower lateral hand position variability during conditions with haptic feedback. They also displayed lower lateral midpoint position variability when they had visual feedback of their partner. For this first experiment, participant hand and midpoint trajectories for the mechanical perturbation trials are shown in Supplemental Material, Section B.

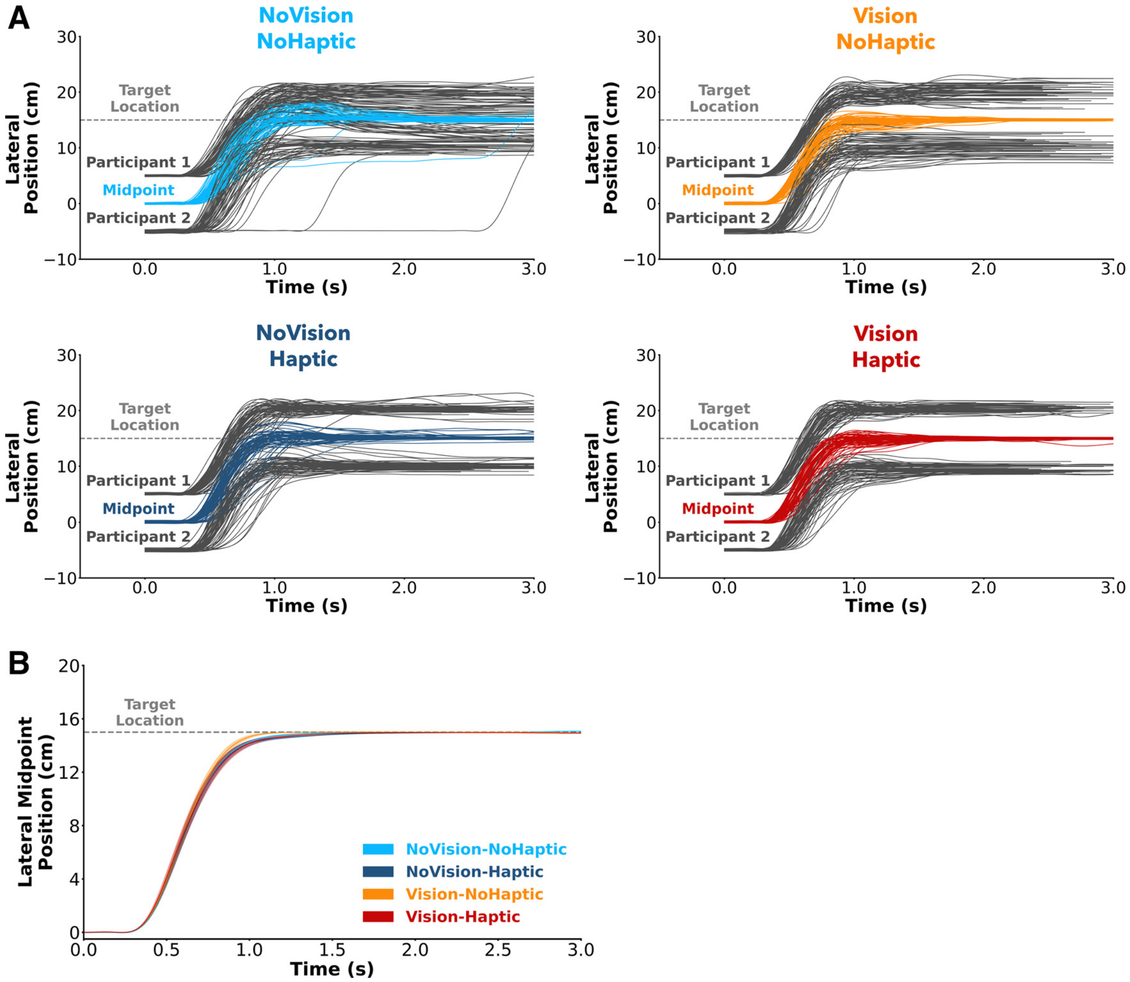

Figure 2. *Experiment 1* participants' hand and midpoint movement behavior. *A*: lateral hand (cursor) position and lateral midpoint position (*y*-axis) over time (*x*-axis) from an exemplar human pair. *Participant 1* and *2* hand trajectories are gray and the midpoint trajectories are colored according to the respective condition. *B*: mean lateral midpoint position (*y*-axis) over trial time (*x*-axis) for each condition. Error ribbons represent ±1 standard error between human pairs.

At the group level, across all human pairs, we show the average lateral midpoint position for the experimental trials (Fig. 2*B*). Participants displayed similar lateral midpoint position across conditions.

Task-relevant and task-irrelevant movement variability.

Similar to previous work (26), we examined movement variability as a metric of state estimation. Specifically, we examined task-relevant movement variability as a metric of whether humans use visual feedback and haptic feedback to perform state estimation of a partner's movements. Task-relevant movement variability corresponds to hand position changes that influence the position of the midpoint. As a reminder, if visual accuracy is more important than shorter haptic time delays for state estimate of a partner, we would expect lower task-relevant movement variability with visual feedback compared with haptic feedback. Conversely, if shorter haptic time delays are more important than visual accuracy for state estimation, we would expect lower task-relevant movement variability with haptic feedback compared with visual feedback.

Figure 3*A* shows task-relevant movement variability across all human pairs over time. We focused on movement variability within the time window between 2.1 and 2.5 s, which aligned with the instructed trial time. For task-relevant movement variability, we found a significant main effect of visual feedback [$F(1,19) = 9.600$, $P = 0.006$]. We did not find a main effect of haptic feedback [$F(1,19) = 4.084$, $P = 0.058$] or an interaction of visual and haptic feedback [$F(1,19) = 1.376$, $P = 0.255$]. We found that task-relevant movement variability was significantly lower in conditions where participants received visual feedback of their partner ($P = 0.003$, $\hat{\theta} = 85.0\%$, Fig. 3*C*). This finding supports the idea that visual accuracy is more important than shorter haptic time delays when estimating the state of a partner during a collaborative sensorimotor interaction.

We also examined task-irrelevant movement variability (Fig. 3*B*). Task-irrelevant movement variability reflects hand position changes that do not influence the position of the midpoint. Such task-irrelevant movement variability is possible because both participants can move their hands at equal distances in opposite directions without changing the position of the midpoint. For task-irrelevant movement variability, we found a significant main effect of haptic feedback [$F(1,19) = 35.130$, $P < 0.001$]. We did not find a main effect of visual feedback [$F(1,19) = 2.508$, $P = 0.130$] or an interaction between visual and haptic feedback [$F(1, 19) = 2.03$, $P = 0.170$]. As shown in Fig. 3*D*, task-irrelevant variability was significantly lower in conditions where participants received haptic feedback of their partner ($P < 0.001$, $\hat{\theta} = 95.0\%$). Lower task-irrelevant movement variability likely reflects task dynamics during conditions with haptic feedback. During these conditions, participants were mechanically linked to their partner with a spring that would increase the likelihood of their hands moving in a similar direction, which would result in lower task-irrelevant movement variability.

Movement smoothness and trial completion time.

Although we were primarily interested in task-relevant movement variability to assess whether humans were performing state estimation of their partner's movement, we also examined movement smoothness and trial completion time. We would expect to find that conditions with comparatively lower task-relevant movement variability would also have smoother movements and an earlier trial completion time. That is, less variable movements are more likely smoother, as well as making it easier to enter and keep the midpoint within the target.

We quantified the movement smoothness of the midpoint by calculating log dimensionless jerk. For midpoint jerk, we found a significant main effect of visual feedback [$F(1,19) = 14.250$, $P = 0.001$]. We did not find a main effect of haptic feedback [$F(1,19) = 0.008$, $P = 0.928$] or an interaction of visual and haptic feedback [$F(1,19) = 0.323$, $P = 0.576$]. Similar to task-relevant movement variability, as shown in Fig. 3*E*, the movement smoothness of the midpoint was significantly greater in the conditions where participants received visual feedback of the partner ($P < 0.001$, $\hat{\theta} = 72.5\%$).

For trial completion time, we also found a significant main effect of visual feedback [$F(1,19) = 9.073$, $P = 0.007$]. We did not find a main effect of haptic feedback [$F(1,19) = 0.023$, $P = 0.881$] or an interaction of visual and haptic feedback [$F(1,19) = 1.376$, $P = 0.255$]. Human pairs on average took slightly longer than the desired 2.1 to 2.5 s trial completion window. As shown in Fig. 3*F*, trial completion was significantly earlier in conditions where the participants received visual feedback of their partner ($P < 0.001$, $\hat{\theta} = 75.0\%$). Both smoother movements and faster trial completion times complement lower task-relevant movement variability, further supporting the idea that visual feedback is used for state estimation of a partner during a collaborative sensorimotor task.

Optimal feedback control model.

We used an optimal feedback control model to predict hand and midpoint trajectories over time. Figure 4*A* shows one simulated human pair for the NoVision-Haptic, Vision-NoHaptic, and Vision-Haptic conditions. As a reminder, we did not simulate the NoVision-NoHaptic condition. The model was able to move the midpoint to the target while capturing hand and midpoint movement variability.

Figure 4, *B* and *C*, respectively, displays task-relevant movement variability and task-irrelevant movement variability over time for 100 simulated human pairs. Similar to the behavioral data (Fig. 3, *A* and *B*), the model predicts greater movement variability during the initial portion of the reach and qualitatively captures differences between conditions. However, the model only showed a modest reduction in task-relevant movement variability with time. Aligned with the behavioral data, the model predicted lower task-relevant movement variability with conditions involving visual feedback (compare Fig. 3*C* with Fig. 4*D*) during the 2.1 to 2.5 s time window. The model considers both visual feedback and haptic feedback to perform state estimation of a partner via a Kalman filter. When considering both sources of feedback, the model predicts and further supports that idea that visual accuracy is more important than haptic speed for lowering task-relevant movement variability during a collaborative sensorimotor interaction.

Similar to human behavior, the optimal feedback control model also predicted lower task-irrelevant variability in

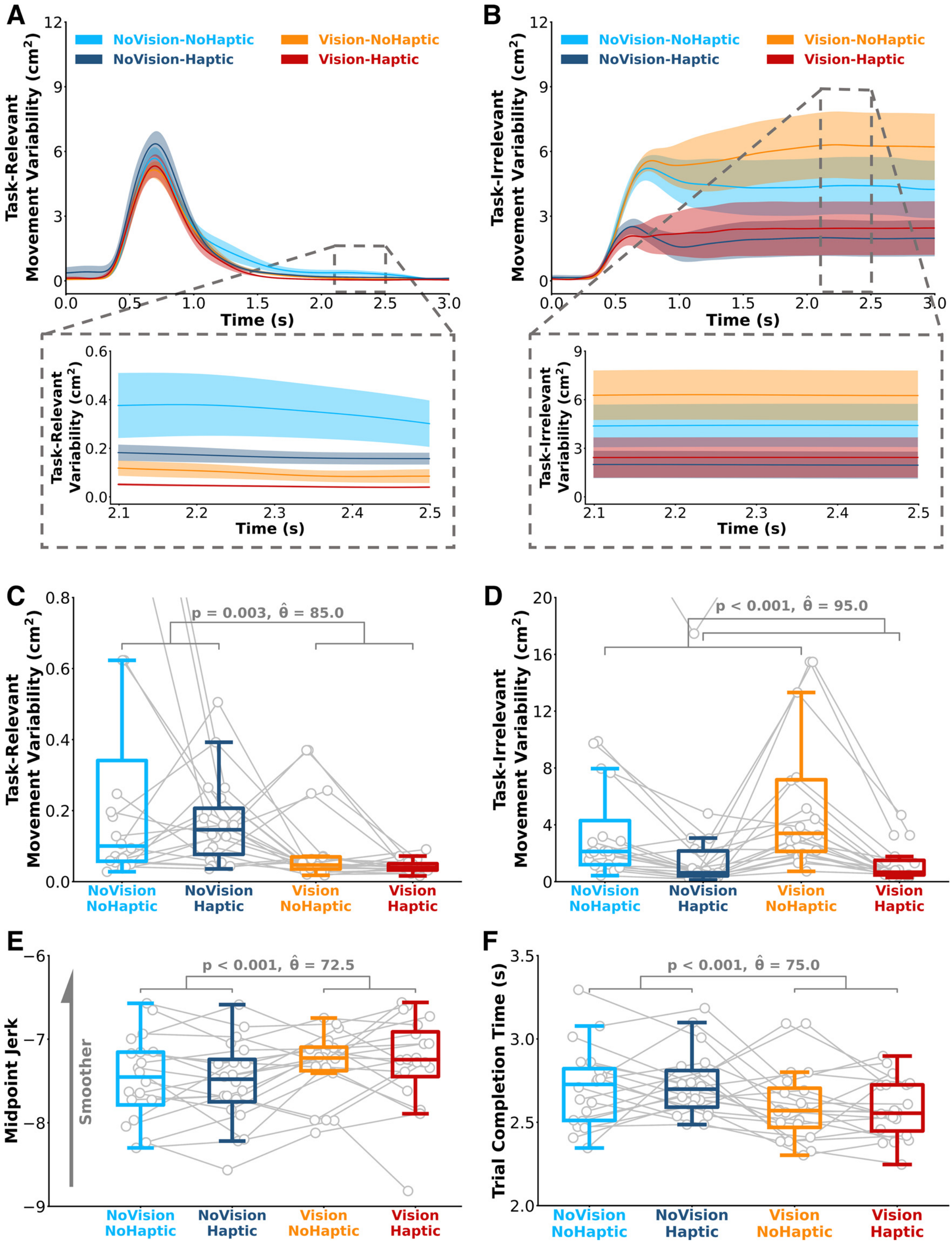

Figure 3. *Experiment 1* movement variability, smoothness, and task performance. Task-relevant movement variability (*y*-axis) (*A*) and task-irrelevant movement variability (*y*-axis) (*B*) over time (*x*-axis) for each condition is shown in the top plots. *A* and *B*: the gray-dashed boxes magnify task-relevant movement variability and task-irrelevant movement variability between 2.1 and 2.5 s, aligned with their instructed trial time. Average task-relevant movement variability (*y*-axis) (*C*) and average task-irrelevant movement variability (*D*) between 2.1 and 2.5 s for each condition (*x*-axis). *E*: average movement smoothness of the midpoint quantified with a log-dimensionless jerk (*y*-axis) for each condition (*x*-axis). *F*: average trial completion time (*y*-axis) for each condition (*x*-axis). Error ribbons represent ±1 standard error between human pairs. Open gray circles and connecting gray lines correspond to a human pair. Box plots show 25th, 50th, and 75th percentiles. Collectively, these results suggest that visual feedback is used for state estimation of a partner and leads to lower task-relevant movement variability, smoother movements, and improved task performance.

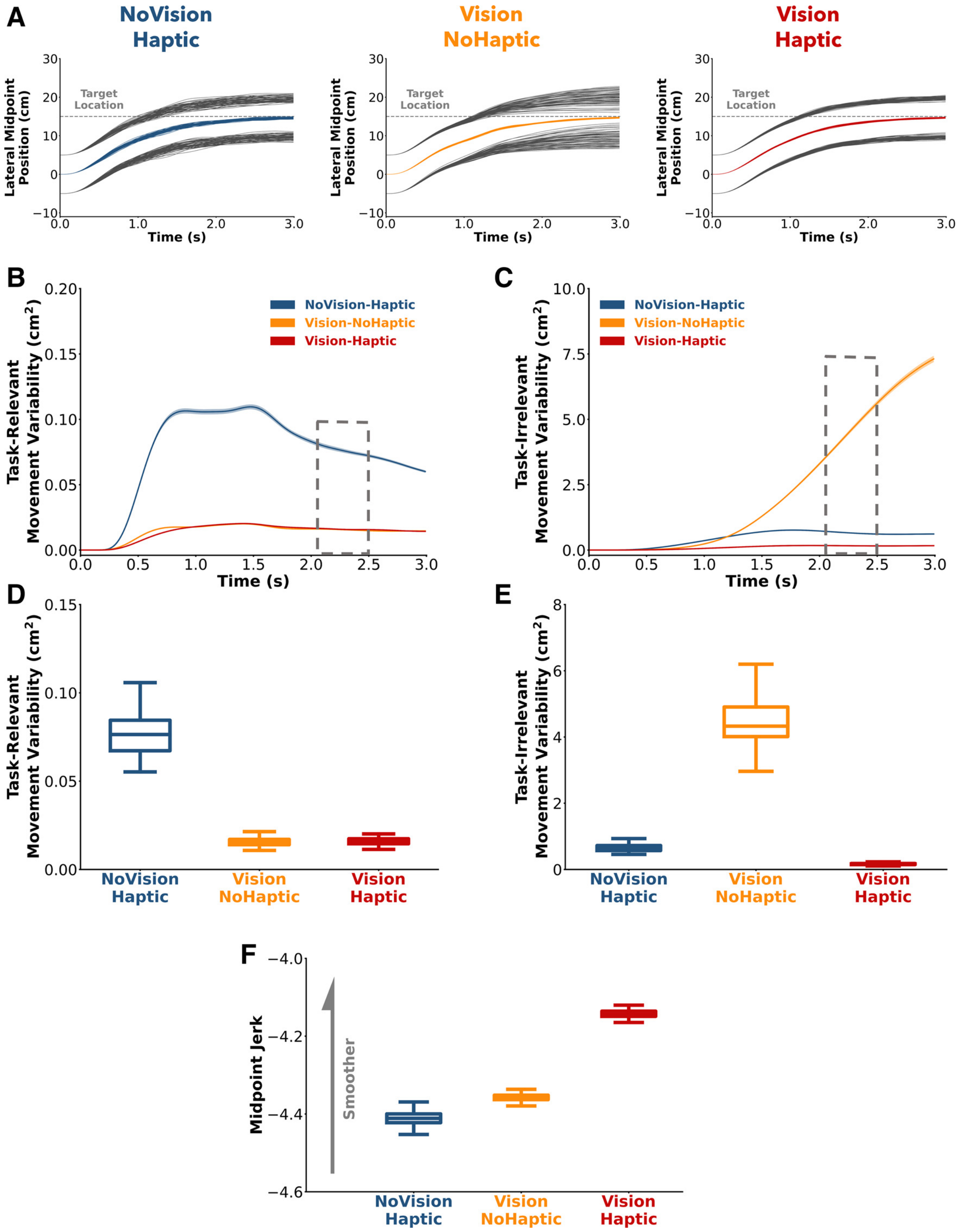

Figure 4. *Experiment 1* optimal feedback control model. Each participant in a human pair was modeled with a separate optimal feedback controller. Together, the two controllers moved the midpoint to a desired target location. Each optimal feedback controller performed state estimation using visual and/or haptic feedback of both self and the partner. Visual feedback was modeled with lower noise and larger time delays compared with haptic feedback. Similar to the experiment, the controllers could not directly observe the states of the midpoint. *A*: lateral hand position and midpoint position (*y*-axis) over time (*x*-axis) from a simulated human pair. Task-relevant movement variability (*y*-axis) (*B*) and task-irrelevant movement variability (*y*-axis) (*C*) over time (*x*-axis) for each condition when simulating 100 human pairs. Average task-relevant movement variability (*y*-axis) (*D*) and task-irrelevant movement variability (*y*-axis) (*E*) from 2.1 to 2.5 s for each simulated condition (*x*-axis). *F*: movement smoothness of the midpoint was quantified using log dimensionless jerk (*y*-axis) for each simulated condition (*x*-axis). Aligned with *experiment 1* results, the optimal feedback controllers predict less task-relevant movement variability with visual feedback (see Fig. 3*C*), lower task-irrelevant movement variability with haptic feedback (see Fig. 3*D*), and smoother movements with visual feedback (see Fig. 3*E*). These results suggest that the higher accuracy of visual feedback is more important than the lower time delays of haptic feedback for state estimation of a partner. Error ribbons represent ±1 standard error and box plots show 25th, 50th, and 75th percentiles between 100 simulated human pairs.

conditions involving haptic feedback provided via a spring (compare Fig. 3*D* with Fig. 4*E*). In addition, we found that visual feedback led to greater movement smoothness of the midpoint (Fig. 4*F*).

Experiment 2

The goal of *experiment 2* was to replicate the results of the first experiment when extending the experimental paradigm to a two-dimensional collaborative reaching task. In *experiment 2*, participants could move their hand in both the lateral and forward direction (Fig. 1*A*). The target was forward relative to the starting position of the jointly controlled midpoint.

Individual and group movement behavior of human pairs.

Hand and midpoint trajectories from an exemplar human pair are shown for each experimental condition (Fig. 5*A*). Generally, this human pair displayed more hand variability than midpoint variability. At the group level, the average forward (Fig. 5*B*) and lateral (Fig. 5*C*) midpoint position over time is shown for each condition. Across conditions, participants displayed similar forward and lateral midpoint positions. For this second experiment, participant hand and midpoint trajectories for the mechanical and visual perturbation trials are shown in Supplemental Material, Section C.

Task-relevant and task-irrelevant movement variability.

As in the first experiment, we again examined task-relevant movement variability as a metric of state estimation. Task-relevant movement variability from all human pairs was plotted over time (Fig. 6*A*). We found a significant main effect of visual feedback on task-relevant movement variability [*F*(1,19) = 5.114, *P* = 0.035], but no main effect of haptic feedback [*F*(1,19) = 1.768, *P* = 0.199] nor an interaction of visual and haptic feedback [*F*(1,19) = 0.921, *P* =

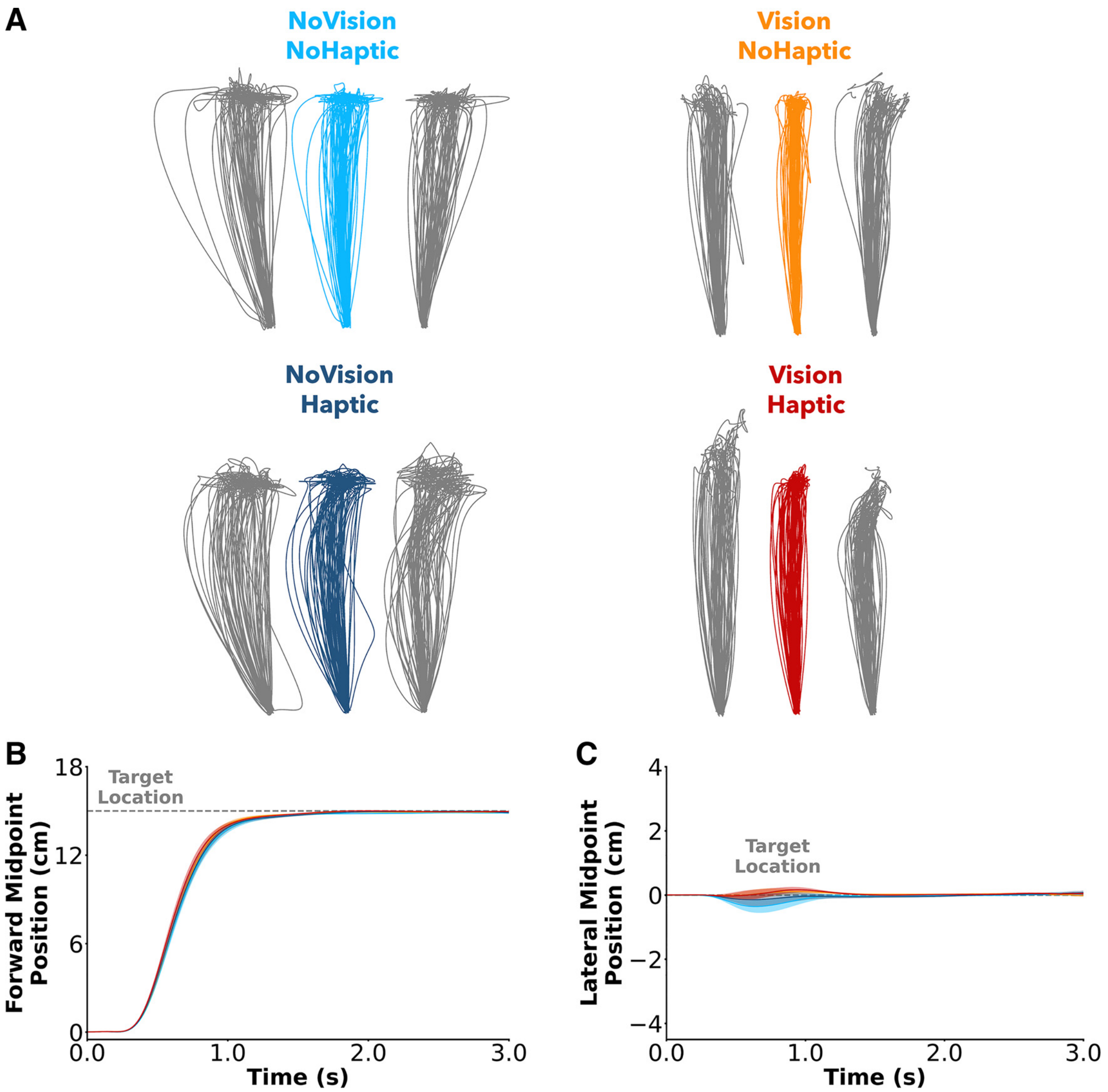

Figure 5. *Experiment 2* participant hand and midpoint movement behavior. *A*: hand trajectories are gray and the midpoint trajectories are colored according to the respective condition. *B*: average forward midpoint position (*y*-axis) over time (*x*-axis). *C*: average lateral midpoint position (*y*-axis) over time (*x*-axis). Error ribbons represent ±1 standard error between human pairs.

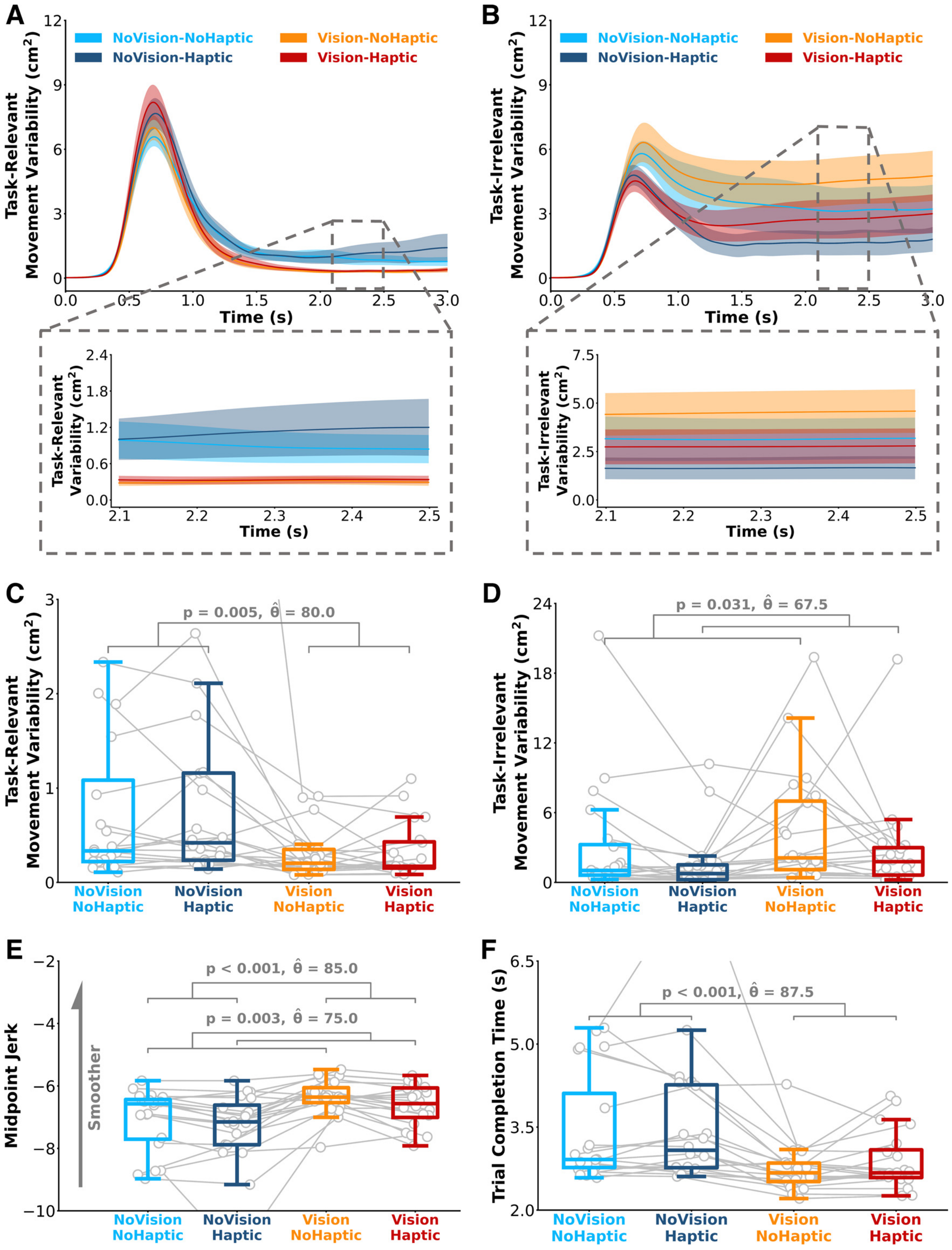

Figure 6. *Experiment 2* movement variability, smoothness, and task performance. Task-relevant movement variability (*y*-axis) (*A*) and task-irrelevant movement variability (*y*-axis) (*B*) over time (*x*-axis) for each condition are shown in the top plots. *A* and *B*: gray-dashed boxes magnify task-relevant movement variability and task-irrelevant movement variability between 2.1 and 2.5 s. Average task-relevant movement variability (*y*-axis) (*C*) and task-irrelevant movement variability (*D*) between 2.1 and 2.5 s for each condition (*x*-axis). *E*: average movement smoothness of the midpoint quantified using log dimensionless jerk (*y*-axis) for each condition (*x*-axis). *F*: average trial completion time (*y*-axis) for each condition (*x*-axis). These results match with *experiment 1* and further support that visual feedback is used for state estimation of a partner, which leads to lower task-relevant movement variability, smoother movements, and improved task performance. Error ribbons represent ±1 standard error between human pairs. Open gray circles and connecting gray lines correspond to a human pair. Box plots show 25th, 50th, and 75th percentile across human pairs.

0.349]. Replicating the results of *experiment 1*, we found that task-relevant variability was significantly lower in conditions where participants received visual feedback of their partner ($P = 0.005$, $\hat{\theta} = 80.0\%$, Fig. 6*C*). Thus, the findings in *experiment 2* further support the idea that visual accuracy is more important than shorter haptic time delays when estimating the state of a partner during a collaborative sensorimotor interaction.

Task-irrelevant movement variability over time is shown in Fig. 6*B*. For task-irrelevant variability, we found a significant main effect of haptic feedback [$F(1,19) = 8.157$, $P = 0.010$]. We did not find a main effect of visual feedback [$F(1,19) = 3.489$, $P = 0.077$] or an interaction of visual and haptic feedback [$F(1,19) = 0.017$, $P = 0.898$]. As in *experiment 1*, task-irrelevant variability was significantly lower in conditions where participants received haptic feedback compared with when they received visual feedback of their partner ($P = 0.031$, $\hat{\theta} = 67.5\%$, Fig. 6*D*).

Movement smoothness and trial completion time.

For movement smoothness, we found a significant main effect of visual feedback on midpoint jerk, [$F(1,19) = 15.810$, $P < 0.001$]. We found that participants had significantly smoother movements for conditions where they had visual feedback of their partner ($P < 0.001$, $\hat{\theta} = 85.0\%$, Fig. 6*E*). We did not find an interaction of visual and haptic feedback on midpoint jerk [$F(1,19) < 0.001$, $P = 0.99$], but did find a significant main effect of haptic feedback [$F(1,19) = 9.574$, $P = 0.006$]. Unlike *experiment 1*, we found movements were less smooth in conditions with haptic feedback ($P = 0.003$, $\hat{\theta} = 75.0\%$). For trial completion time, we found a significant main effect of visual feedback [$F(1,19) = 13.01$, $P = 0.002$], but did not find a main effect of haptic feedback [$F(1,19) = 2.087$, $P = 0.165$] nor an interaction of visual and haptic feedback [$F(1,19) = 0.001$, $P = 0.977$]. Aligned with the findings of *experiment 1*, trial completion times were significantly earlier in the conditions where the participants received visual feedback of their partner ($P < 0.001$, $\hat{\theta} = 87.5\%$, Fig. 6*F*). Aligning with results from *experiment 1*, human pairs had displayed smoother midpoint trajectories and had earlier trial completion times when the participants received visual feedback of their partner.

Optimal feedback control model.

We used the same optimal feedback control model to capture the results of *experiment 2*. Predicted hand trajectories and midpoint trajectories from one simulated human pair are shown for each feedback condition (Fig. 7*A*). Task-relevant movement variability (Fig. 7*B*) and task-irrelevant movement variability (Fig. 7*C*) across simulated human pairs were plotted over time. Matching the behavioral findings of *experiment 2*, model predicted task-relevant movement variability between 2.0 and 2.5 s was smaller with visual feedback of a partner (compare Fig. 6*C* with Fig. 7*D*). Likewise, model predicted task-irrelevant movement variability was smaller in haptic feedback conditions (compare Fig. 6*D* with Fig. 7*E*). In addition, similar to *experiment 2*, the model predicted smoother movement of the midpoint when there was visual feedback of the partner (compare Fig. 6*E* with Fig. 7*F*).

Collectively, *experiment 1*, *Experiment 2*, and our computational model showed decreased task-relevant movement variability and smoother midpoint movements with visual feedback of a partner. We also found earlier trial completion times during conditions with visual feedback. Taken together, our findings support the idea that visual accuracy is more important than short haptic time delays when estimating the state of a partner during collaborative sensorimotor interactions.

DISCUSSION

Our primary finding across the two experiments was that human pairs displayed lower task-relevant movement variability during conditions where they had visual feedback of their partner. Matching the behavioral results, the optimal feedback control model predicted lower task-relevant movement variability in conditions where there was visual feedback of a partner. The model considered the unique sensory noise and time delays of both visual feedback and haptic feedback to perform state estimation of a partner. Taken together, our empirical results and computational modeling support the idea that the lower noise of visual feedback is more important than the shorter time delays of haptic feedback when estimating the state of a partner during collaborative sensorimotor tasks.

In this paper, we demonstrated the role of both visual feedback and haptic feedback of a partner when human pairs performed a collaborative sensorimotor reaching task. In *experiment 1*, we constrained the reaching movements of a human pair to the lateral dimension. *Experiment 2* allowed for reaching movements along both the forward and lateral dimensions and replicated several key findings of *experiment 1*. Task-relevant variability was examined within a time window when the participants attempted to maintain the jointly controlled midpoint inside the target. We found in both experiments that the visual feedback of a partner led to lower task-relevant movement variability. We would expect that lower task-relevant movement variability would lead to smoother midpoint movements, as well as make it easier to enter and stabilize the midpoint within the target. Indeed, complementing lower task-relevant movement variability, in both experiments we found that participants displayed smoother midpoint movements and faster trial completion times when participants had visual feedback of their partner. Our optimal feedback control model was able to predict relatively lower task-relevant movement variability and smoother movements when simulating conditions with visual feedback of a partner. The model was able to capture lower task-relevant movement variability and smoother movements by using a state estimator that considered sensory noise and time delays of visual and haptic feedback. Unexpectedly, in both experiments, the presence of haptic feedback did not reduce task-relevant movement variability. However, we found that task-irrelevant movement variability was lower when participants had haptic feedback of their partner, which was also captured by the optimal feedback control model and likely caused by spring dynamics that increased the possibility of their hands moving in a similar direction. Collectively, *experiment 1*, *experiment 2*, and the optimal feedback control model suggest that humans rely primarily on high visual accuracy, rather than faster yet noisier

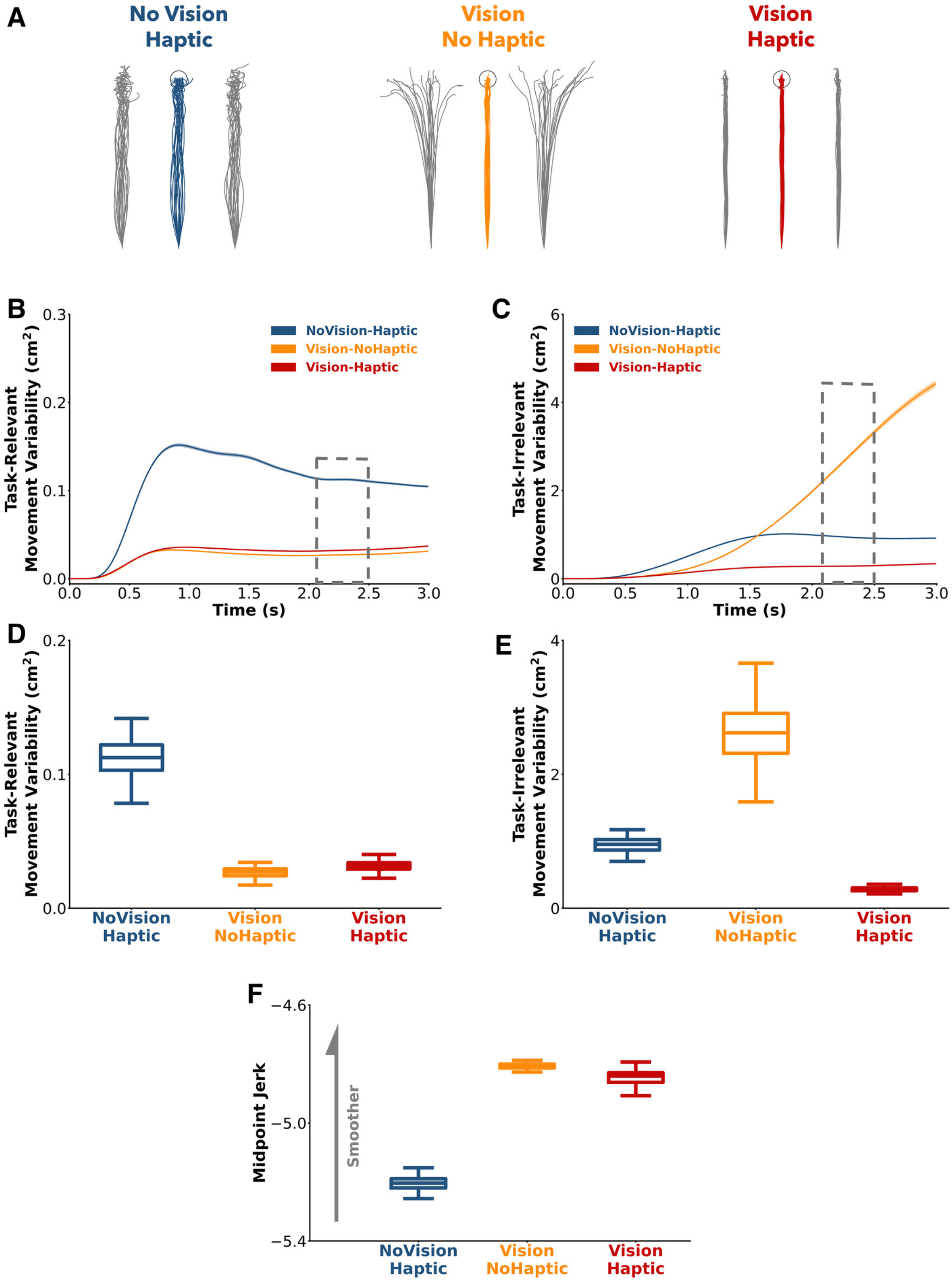

Figure 7. *Experiment 2* optimal feedback control model. We used the same model from *experiment 1* to predict the results in *experiment 2*. *A*: hand and midpoint trajectories for one simulated human pair. Task-relevant movement variability (*y*-axis) (*B*) and task-irrelevant movement variability (*y*-axis) (*C*) over time (*x*-axis) for each simulated condition. Average task-relevant movement variability (*y*-axis) (*D*) and task-irrelevant movement variability (*E*) between 2.1 and 2.5 s for each condition (*x*-axis). *F*: movement smoothness of the midpoint quantified using log dimensionless jerk (*y*-axis) for each condition (*x*-axis). Matching the behavioral results of *experiment 2* (see Fig. 6), the optimal feedback controllers predicted less task-relevant movement variability with visual feedback, lower task-irrelevant movement variability with haptic feedback, and smoother movements with visual feedback. Error ribbons represent ±1 standard error and box plots show 25th, 50th, and 75th percentiles between 100 simulated human pairs.

haptic feedback, to perform state-estimation of their partner during collaborative sensorimotor tasks.

The uncontrolled manifold analysis has been used extensively to separate task-relevant and task-irrelevant movement variability in the joint space of a single individual (34, 49). However, to our knowledge, this approach has not been applied to study human-human sensorimotor interactions during reaching. In our experiments, task-relevant movement variability corresponds to hand position changes that influence the position of the midpoint. Conversely, task-irrelevant movement variability reflects hand position changes that do not influence the position of the midpoint, such as when participants move their hands at equal distances in opposite directions without changing the position of the midpoint. We found a lower task-relevant movement variability when participants had visual feedback of their partner. Lower task-relevant movement variability when participants have visual feedback of their partner aligns with past work that examined the role of feedback during single-person reaching experiments (26). In a target-reaching task, Kasuga et al. (26) found that the hand movement variability at the target was lower when participants had visual feedback of their hand and proprioceptive feedback of their limb compared with when participants relied only on proprioception feedback. They showed that these results were consistent with a dynamic Bayesian integration model (i.e., Kalman filter) that weighted visual and proprioceptive feedback according to their sensory acuities and time delays. The central idea of Bayesian multisensory integration is that a combined state estimate from visual feedback and haptic feedback is better than relying solely on either sensory modality (8, 9). However, in both our experiments, we did not find a significant interaction between visual and haptic feedback. A possible reason could be that visual accuracy was much greater than haptic accuracy, leading to a very large weighting for visual feedback during multisensory integration. Note that we did not directly quantify the multisensory integration of the presented haptic and visual feedback using response time methods (50). Although feedback delays on the order of tens of milliseconds cannot be ignored for feedback control in humans (42), we did not find that smaller haptic time delays led to improved collaborative performance. Rather, our results suggest that visual feedback is the dominant form of sensory feedback used to jointly coordinate actions with another human.

Past work has repeatedly shown in single-participant studies that task-irrelevant movement variability is greater than task-relevant movement variability in joint space (34, 51). Similarly, in each condition of both experiments, it is readily observable that task-irrelevant movement variability was larger than task-relevant movement variability. From an optimal control standpoint, the minimum intervention principle (52) supports this finding because hand deviations from the average hand movements need to be corrected only when they interfere with the movement goal. That is, one would only make hand movement changes that led to the midpoint reaching the target. It has been posited that a higher task-irrelevant movement variability represents the ability of our central nervous system to generate flexible movement solutions and is useful for motor learning and exploration (47, 53–56). Extending results from single-person experiments, our findings on task-irrelevant movement variability demonstrate similar flexibility in movement coordination between multiple humans during sensorimotor collaboration. However, the ability of the participants to flexibly adapt movement solutions was reduced with haptic feedback. Specifically, task-irrelevant movement variability was lower when participants had haptic feedback of their partners. Lower task-irrelevant movement variability is likely an outcome of the mechanical coupling created by the spring connecting the hands of the participants. Participants could not as flexibly move their hands in equal and opposite directions without affecting the movement of the midpoint when there was a spring between their hands, even though we purposely used a relatively compliant spring that still yielded perceptual differences in haptic forces acting upon the hand. It is unclear if reducing the ability of humans to freely choose movement solutions along the task-irrelevant dimension influenced learned collaborative behavior (57). Similar to results for task-relevant movement variability, there was no evidence of multisensory integration of haptic feedback and visual feedback for task-irrelevant movement variability. Particularly, task-irrelevant movement variability was similar when participants had only haptic feedback compared with both visual and haptic feedback. Future studies could address the role of task-irrelevant movement variability for motor exploration and learning during sensorimotor collaboration between humans, and the related implication of enabling haptic feedback through a mechanical connection.

Smooth movements indicate good spatiotemporal coordination (39) and minimization of movement effort (58). Several studies have used movement smoothness measures to quantify upper limb and lower limb movement performance within an individual (37, 59–62). In this work, we examined how visual and haptic feedback of the partner affected the movement smoothness of the midpoint. To quantify movement smoothness, we used the log dimensionless jerk metric that is robust to differences in movement durations and movement velocities (38, 39). We found that the movements of the midpoint were smoother when participants had visual feedback of their partner. Similar to task-relevant movement variability, a more accurate state estimate of the midpoint with visual feedback of the partner likely resulted in smoother movements. In addition, more accurate state information with visual feedback could have also led to participants predicting their partner's actions. It would be interesting for subsequent work to examine how accurate state information could further promote predicting a partner's actions.

Unlike results from the first experiment, we also found in the second experiment that movements were less smooth when participants had haptic feedback of their partner. The movements of the midpoint might have been slightly less smooth with haptic feedback due to small oscillatory forces caused by the spring. The oscillatory effects of the spring could be minimized by adding a damper in parallel to the spring. Task completion times can also be explained from a state estimation point of view. Since visual feedback afforded a better state estimate of the midpoint, participants took less time to stabilize the midpoint within the target. Across the two experiments, we observed lower task-relevant movement variability when participants had visual feedback of the partner. Lower task-relevant movement variability likely contributed to smoother movements and faster completion times. Thus, lower task-relevant movement variability, smoother movements, and faster completion times with visual feedback collectively support the idea that humans primarily rely on visual accuracy to estimate the state of their partner. It would be interesting to manipulate visual noise and visual time delays to further test the role of visual feedback on estimating the state of another human during collaborative, cooperative, or competitive tasks.

Numerous studies have reported that haptic feedback of the partner enhances individual performance (10–12, 31) or collaborative performance (2, 13, 63–65). Across the aforementioned studies, a virtual spring mechanically linked the hands of two or more humans to enable haptic feedback. The central proposition of these studies is that haptic feedback serves as a way to communicate and integrate information about each other's interpersonal task goals. For instance, Takagi et al. (11, 12, 31) measured individual tracking performance when an individual or multiple participants attempted to keep a cursor, aligned with their hand, over a moving target. During conditions with two or more participants, haptic feedback was enabled by connecting the hands of the participants with a virtual spring. Performance was measured as the integrated difference between an individual's cursor and the moving target. They found individuals displayed improved performance when they were connected to another person compared with when they did the task alone. Performance improvement for these studies was attributed to participants using haptic feedback to obtain a better estimate of interpersonal goals. While possible, an alternative explanation is that participants could have displayed improved performance simply due to the dynamics of the task. That is, participants may have had better individual performance when virtually connected to another person simply because whenever they started to deviate from the moving target, the other person would pull their hand closer to the target via haptic forces caused by the virtual spring.

In our experiments, enabling haptic feedback did not have an influence on task performance that would indicate state estimation of a partner or integrating interpersonal goals. Rather, the presence of haptic feedback only seemed to influence task-irrelevant movements that did not influence task performance. Here, the spring mechanically limited kinematically redundant movement solutions. A potential limitation of using a virtual spring to enable haptic feedback is that the forces caused by the spring can influence movement during the task. In addition, participant may have unique feedback responses to external mechanical perturbations that may alter spring forces. Such spring forces could be avoided by alternatively adopting haptic vibrations (66–68). However, such vibratory haptic feedback does not commonly occur in naturalistic interactions and would likely be complex to interpret. Nevertheless, in our experimental task, the findings would suggest that the high sensory noise of haptic feedback limits its role to provide state estimation of a partner. However, in other tasks, it is possible that haptic feedback can be used to learn optimal coordination strategies (13, 22, 30, 69, 70) or enhance the performance of less skilled partners (10–12, 31, 71–73). Future studies should attempt to separate the role of haptics as a state estimator or changing task dynamics since both can influence task performance.

The optimal feedback control framework (20) has been used previously to model sensorimotor interactions between humans. The models proposed in the literature have focused on how individuals use haptic feedback of a partner to form representations of their partner's movement goals and actions (12, 13, 22, 31). Chackochan and Sanguineti (13) showed that participants and an optimal feedback control model converged into an optimal game-theoretic collaborative strategy. They also showed that when visual feedback is added to haptic feedback participants had improved joint performance. Yet this and other prior work did not address how the unique sensory noise and time delays of visual feedback and haptic feedback might influence task performance. We are the first to develop a computational model to examine the roles of visual and haptic feedback of a partner during sensorimotor collaboration between humans. For the feedback controller, we utilized iLQR (41) since the model dynamics were nonlinear. For state estimation, we designed an extended Kalman filter (44, 45) to include the sensory acuities and time delays of visual feedback and haptic feedback (7, 9).

Supporting the findings of both *experiment 1* and *experiment 2*, our model predicted condition differences of task-relevant movement variability and movement smoothness by using visual feedback and/or haptic feedback to estimate the state of a partner. Higher accuracy of visual feedback dominated over less delayed yet noisier haptic feedback for state estimation of the partner and consequently the midpoint. It also predicted lower task-irrelevant movement variability with haptic feedback since we included the dynamics of the spring. Unlike the results from the experiments, our model predicted slightly lower task-irrelevant movement variability with both haptic feedback and visual feedback compared with only haptic feedback. This result is likely due to a combination of the dynamics created by haptic feedback and better sensory estimation enabled by visual feedback. For simplicity, and similar to others modeling interactive behavior (13, 31), the model did not incorporate signal-dependent noise (43, 58). Including signal-dependent noise would likely increase and then decrease task-relevant and task-irrelevant movement variability during the middle and end portions of the reach, respectively. Participants utilized feedforward strategies especially when performing the task in the absence of visual feedback of their partner. We did not model such feedforward strategies since our primary focus was on understanding the state estimation of a partner. However, it may be possible to capture feedforward strategies by considering reinforcement learning algorithms, presenting another avenue to study collaborative sensorimotor interactions. Nevertheless, despite some limitations, our model captured the main findings from the experiments and further supports the idea that high visual accuracy is important to estimate the state of a partner.

How humans utilize sensory feedback of others is relevant for sensorimotor interactions that are common in everyday life, during competitive interactions (74), and neurorehabilitation (4). Our work advances the understanding of how humans utilize visual feedback and haptic feedback of a partner during sensorimotor collaboration. Across two experiments and supported by a computational model, we showed that humans rely primarily on high visual accuracy to estimate the state of their partner and improve joint performance. We suggest the use of visual feedback over haptic feedback for providing positional state information of interacting individuals. Furthermore, when haptic feedback is enabled, it is important to consider the influence of haptic forces that can influence sensorimotor coordination and learning. Insights gained from our work may be applied to develop control architectures for physical human-robot interaction, with a large range of applications that span exoskeletons to reduce occupational injuries, assistive driving, surgical skill training, and robot-mediated neurorehabilitation.

DATA AVAILABILITY

Data will be made available upon reasonable request.

SUPPLEMENTAL DATA

Supplemental sections: https://doi.org/10.6084/m9.figshare.22704598.

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DISCLOSURES

No conflicts of interest, financial or otherwise, are declared by the authors.

AUTHOR CONTRIBUTIONS

R.L., M.J.C., and J.G.A.C. conceived and designed research; R.L., L.S.G., T.N., and V.R.F.M. performed experiments; R.L. analyzed data; R.L., S.R.S., A.M.R., J.A.C., J.B., M.J.C., and J.G.A.C. interpreted results of experiments; R.L. and J.G.A.C. prepared figures; R.L. and J.G.A.C. drafted manuscript; R.L., S.R.S., L.S.G., A.M.R., J.A.C., J.B., T.N., V.R.F.M., M.J.C., and J.G.A.C., edited and revised manuscript; R.L., S.R.S., L.S.G., A.M.R., J.A.C., J.B., T.N., V.R.F.M., M.J.C., and J.G.A.C. approved final version of manuscript.

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