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The role of haptic feedback when manipulating nonrigid objects

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Danion F, Diamond JS, Flanagan JR. The role of haptic feedback when manipulating nonrigid objects. *J Neurophysiol* 107: 433–441, 2012. First published October 19, 2011; doi:10.1152/jn.00738.2011.—Humans can learn to manipulate objects with complex dynamics, including nonrigid objects with internal degrees of freedom. The first aim of this study was to assess the contribution of haptic feedback when learning to manipulate a nonrigid object. The second aim was to evaluate how learning without haptic feedback influences subsequent learning with haptic feedback and vice versa. The task involved moving a simulated mass—attached to a grasped handle via a simulated, damped spring—to a target as quickly as possible. In the haptic plus vision (HV) condition, appropriate forces were applied to the handle, which was attached to a robot. In the vision only (V) condition, these forces were turned off. Participants completed 80 trials in each condition, with one-half starting with the HV condition. Both groups exhibited significant learning, as measured by movement time, in both conditions. For the condition performed first, initial performance, learning rate, and final performance were better with haptic feedback. Prior experience in the HV condition led to faster learning and better final performance in the V condition. However, prior experience in the V condition led to slower learning and worse final performance in the HV condition. In the V condition, all participants tended to keep the mass close to the hand. In the HV condition, participants who started with the HV condition allowed the mass to move away from the hand, whereas participants who started with the V condition continued to keep the mass close to the hand. We conclude that haptic feedback as well as prior experience with haptic feedback enhance the ability to control nonrigid objects and that training without haptic feedback can lead to persisting detrimental effects when subsequently dealing with haptic feedback.

object manipulation; motor learning; vision; human

SKILLFUL OBJECT MANIPULATION, including tool use, requires knowledge of the dynamics of the object relating applied force to motion (Flanagan et al. 2006; Johansson and Flanagan 2009). People are highly skilled at predicting and controlling the motion of grasped objects with familiar dynamics, including rigid objects with inertial and elastic loads, where the force applied to the hand is proportional to the acceleration and position of the object, respectively (Flanagan and Wing 1993, 1995, 1997; Westling and Johansson 1984). People are also capable of effectively manipulating many nonrigid objects with internal degrees of freedom, such as a yoyo or a paddleball consisting of a ball attached to a paddle by a spring. It has been postulated that to formulate an appropriate strategy for controlling such an object, the operator must learn an internal model of the object's dynamics, specifying the mapping between forces applied to the object and its motion (Dingwell et al. 2004). Such learning can be challenging, because the motion of the controlled object (e.g., the ball of a paddleball) is governed indirectly through the interaction of the motion of the hand with the internal dynamics of the object and is not yoked to hand motion.

Moving nonrigid objects normally involves interaction forces at the hand. However, in virtual environments, ranging from video games to surgical simulators, such forces are often absent, and therefore, appropriate haptic feedback is unavailable. Previous studies have shown that people can learn to control nonrigid objects both when appropriate haptic feedback is provided (Dingwell et al. 2002, 2004; Nagengast et al. 2009) and when it is not (Mah and Mussa-Ivaldi 2003; Mehta and Schaal 2002). However, it remains unclear whether appropriate haptic feedback improves learning and control. The primary objective of the current study was to assess the influence of haptic feedback in learning to control a nonrigid object. On the one hand, we might expect the provision of appropriate haptic feedback to improve learning and control, because such feedback should improve sensory estimates of the state of the object through multisensory integration (Ernst and Banks 2002; Ernst and Bülthoff 2004; van Beers et al. 2002). Moreover, it has been argued that the ability to predict the consequences of one's actions—an important component of sensorimotor control (Shadmehr et al. 2010; Wolpert and Flanagan 2001)—can be impaired when efference copy and sensory feedback are inconsistent with a particular movement context (Blakemore et al. 1998). On the other hand, the benefit of haptic feedback is not obligatory. With the use of a task in which participants had to control the position of a ball on a rotating beam, Huang and colleagues (2006) found virtually no benefit of haptic information. Specifically, participants with vision only (V) began and finished training with comparable performance with those who also had haptic feedback. In addition, because interaction forces must be taken into account to achieve the desired motion of the hand, it is also possible that the provision of appropriate haptic feedback degrades hand-motion control (and thus object control). Altogether, whether haptic feedback helps, hinders, or simply does not affect the control of nonrigid objects remains an open question.

We were also interested in how learning to control a nonrigid object without haptic feedback influences motor learning and control when haptic feedback is subsequently provided and vice versa. From an applied perspective, this question was motivated by the fact that provision of haptic feedback in virtual reality (VR) simulators is often difficult and costly. As a consequence, determining how training without haptic feedback (i.e., with vision only) influences performance when subsequently dealing with haptic feedback is important. From

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a theoretical perspective, we reasoned that if participants learn a direct mapping between arm motor commands and object motion, we might expect (bidirectional) negative transfer, because this mapping will change depending on whether interaction forces are present. However, it is also possible that participants could learn two distinct mappings when learning to control the object: a mapping between hand motion and object motion, which does not depend on the presence or absence of interaction forces applied to the hand, and a mapping between arm motor commands and hand motion, which does depend on interaction force. In the scenario, it is possible that bidirectional, positive transfer would occur, because the two conditions share a common mapping. However, bidirectional, negative transfer could also occur, because the mapping between arm motor commands and hand motion differs between tasks. Finally, independently of learning dynamics, it is possible that participants adopt different control strategies depending on the initial feedback condition they experience. If they persist with a given strategy when the feedback condition changes, then transfer between conditions may either be positive or negative depending on the efficacy of the strategies selected.

We examined the role of haptic feedback using a task in which participants were asked to move a mass, attached to a hand-held handle via a slightly damped spring, to a target as quickly as possible (Dingwell et al. 2002, 2004; Nagengast et al. 2009). The object was simulated using a VR setup, allowing us to remove appropriate haptic feedback by turning off the forces applied to the handle (but not the simulated mass). Two groups of participants performed the task with visual and haptic feedback (HV task) and with visual feedback only (V task) but in different orders. We assessed initial performance, learning rate, and final performance in both naïve participants, experiencing one of the two tasks for the first time, and participants who previously experienced the other task.

MATERIALS AND METHODS

Participants. Twenty self-proclaimed, right-handed participants (six males and 14 females) took part in this study. Participants were split in two groups (group HV-V: age = 20.7 ± 2.1 yrs, height = 1.70 ± 0.11 m, mass = 58.6 ± 10.5 kg; group V-HV: age = 21.5 ± 2.5 yrs, height = 1.69 ± 0.09 m, mass = 65.6 ± 14.8 kg) who performed the same experimental conditions but in a different order. All participants were healthy and gave informed consent prior to the study. A local university ethics board approved the experiments, which complied with the Declaration of Helsinki.

Apparatus. In a fully illuminated room, participants were required to move a cylindrical object held between the tips of the thumb and the index finger of their right hand. The object had two parallel, horizontal grip surfaces (2.5 cm in diameter), located 6.4 cm apart, and was instrumented with two, six-axis force transducers (Nano force/torque, ATI Industrial Automation, Apex, NC), which measured forces (0.05 N resolution) and torques applied by the thumb and index finger in three dimensions. The two grip surfaces were covered with sandpaper and were free to spin about the long axis of the object, which was attached to a lightweight robotic manipulator (Phantom 3.0 haptic interface, Sensable, Wilmington, MA) via a joint that allowed rotation about all axes except the long axis of the object. Thus the combination of this joint and the spinning grip surfaces allowed free rotation of the object in three dimensions. Three optical encoders, placed on the three motors of the manipulandum, measured the object's position in three dimensions (0.1 mm resolution). Cuffs mounted on air sleds supported the wrist and forearm and restricted motion of the hand to a horizontal plane (Fig. 1). All signals were recorded at a 1,000 Hz sampling frequency.

The positions of the hand (i.e., the grasped object), the virtual mass-spring object, the start position, and the target were all displayed in the horizontal plane of the center of the grasped object using a visual display system (Fig. 1). This system consisted of a 30-inch monitor positioned horizontally above a mirror located half-way between the monitor and plane of hand movement. Participants viewed the visual scene displayed on the monitor via the mirror, which blocked vision of the actual hand and grasped object. Filled circles were used to represent the positions of the hand (blue, 10 mm in diameter), object (yellow, 20 mm in diameter), start position (green, 20 mm in diameter), and target (green, 40 mm in diameter). The simulated properties of the mass-spring object were the following: mass = 3 Kg, stiffness = 120 N/m, damping = 1 N/m/s, resting length = 0 m. Note that these parameter settings are similar to those used in previous studies using this task (Dingwell et al. 2002, 2004; Nagengast et al. 2009). The resonant frequency of this mass-spring system was close to 1 Hz. The dynamics of the mass-spring object were specified as two-dimensional, meaning that lateral displacements of the hand and object were also taken into account for the simulation.

Procedure. At the beginning of each trial, the participant had to first position the hand circle, without the mass-spring attached, over the start position for 300 ms. At this point in time, the target was displayed 15 cm away from the start position, the mass-spring object was displayed, and the simulation of the mass-spring was initiated. Initially, the mass-spring object was aligned with the hand position and the latter displayed on top of the object. Depending on the experimental condition, simulated interaction forces were either applied to the hand or not (see below). The participants were instructed to bring the circles representing the hand and object over the target circle as quickly as possible. However, they were free to initiate their movement when ready, once the target was presented. To complete a trial successfully, both the hand and object had to be within the target with their speed below 2 cm/s for at least 150 ms (Dingwell et al. 2002). At the end of each trial, the resulting movement time (MT) was displayed on the right side of the target. MT was defined as the time interval between the instant that hand speed first exceeded 2 cm/s and the instant at which the trial was completed. As soon as the trial was completed, the simulated mass-spring object was removed from view and turned off. Participants were given a maximum time of 10 s to complete each trial, after which, the trial was aborted. They were encouraged to explore various movements in an effort to minimize MT. However, no specific suggestions were provided.

All participants started the experiment with 10 trials, without the mass-spring object attached to the hand so as to become familiar with

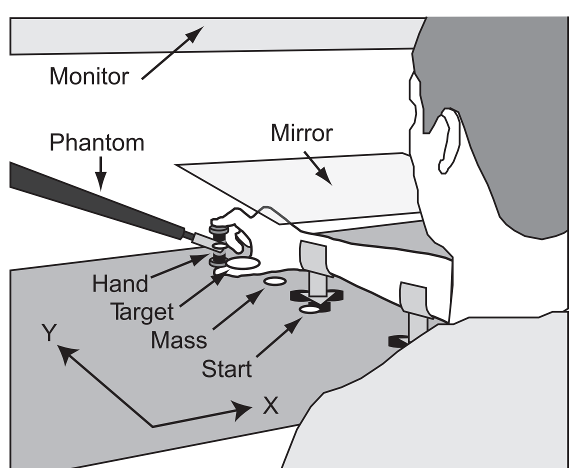

Fig. 1. Schematic drawing of the experimental setup (see MATERIALS AND METHODS for further information).

the goal of the task, the location, and timing of the targets and receiving feedback about MT. Afterwards, participants in the HV-V group completed a block of 80 trials, in which both haptic and visual feedback was provided (HV task). Following a short break of 2–3 min, these participants performed another block of 80 trials, in which haptic feedback was removed, but visual feedback was preserved (V task). Participants of the V-HV group performed the same two blocks of trials but in the opposite order with a similar break in between. Before each block, the participant was informed about the nature of the task and the sensory context (haptic/no haptic). Overall, each participant performed a total of 170 trials (10 + 80 + 80), which on average, took about 45 min. Participants could request additional breaks at any time, but most of them only took the break offered between the two versions of the task.

Data analysis. All kinematic and kinetic signals were low-pass filtered at 20 Hz (fourth-order, no-lag, dual-pass Butterworth filter). For each trial or movement, we computed the MT, the average distance between the hand and object in the Y direction (aligned with the vector from the start position to the target), and the number of crossings between the Y positions of the hand and object. To assess the participants' ability to predict the dynamics of the mass-spring system in the HV task, we measured the coefficient of correlation between grip force and load force (Danion and Sarlegna 2007; Flanagan and Wing 1997). Grip force was computed as the average of the normal forces at the two grip surfaces. To compute load force, we first determined, for each grip surface, the resultant of the two tangential forces, and we then summed these resultant forces. ANOVA was used to assess the effects of task, group, and trial block (using eight blocks of 10 trials for each task). The Newman-Keuls technique was used for post hoc *t*-tests to correct for multiple comparisons. Since correlation coefficients do not follow a normal distribution, z scores (Fisher transformation) were used for statistical analysis. A 0.05 significance threshold was used for all analyses.

To assess learning more specifically, we fit an exponential of the form $y = ae^{bx} + c$ to the MT data. To test for the effects of group, task, and interaction between group and task on the parameters of the exponential fits, we used nonlinear regression with dummy variables to code for group and task. The full model (including main effects and interactions) is given by

$$MT = (a_0 + a_1T + a_2G + a_3TG)e^{(b_0+b_1T+b_2G+b_3TG)block} + (c_0 + c_1T + c_2G + c_3TG)$$

where T and G are dummy variables coding for task ($T = 0$ for the HV task; $T = 1$ for the V task) and group ($G = 0$ for the HV-V group; $G = 1$ for the V-HV group), respectively. Note that this 12-parameter model corresponds to fitting separate, three-parameter exponentials to each combination of group and condition. Benchmarking was used to determine the best-fit model (see RESULTS).

RESULTS

MT analysis. There was no significant difference between the two groups of participants in terms of the mean MT computed over the 10 practice trials ($F_{1,\ 18} = 0.09$; $P = 0.75$). This result suggests that the two groups were similar in overall motor skill.

Figure 2 shows MT as a function of trial block for each group and condition. Each point represents the mean MT, averaged across trials within a block, for a single participant. Benchmarking revealed that the best-fit exponential model (fit to all of the data from both groups and both tasks), in which all parameters were significantly different ($P < 0.05$) than zero, was

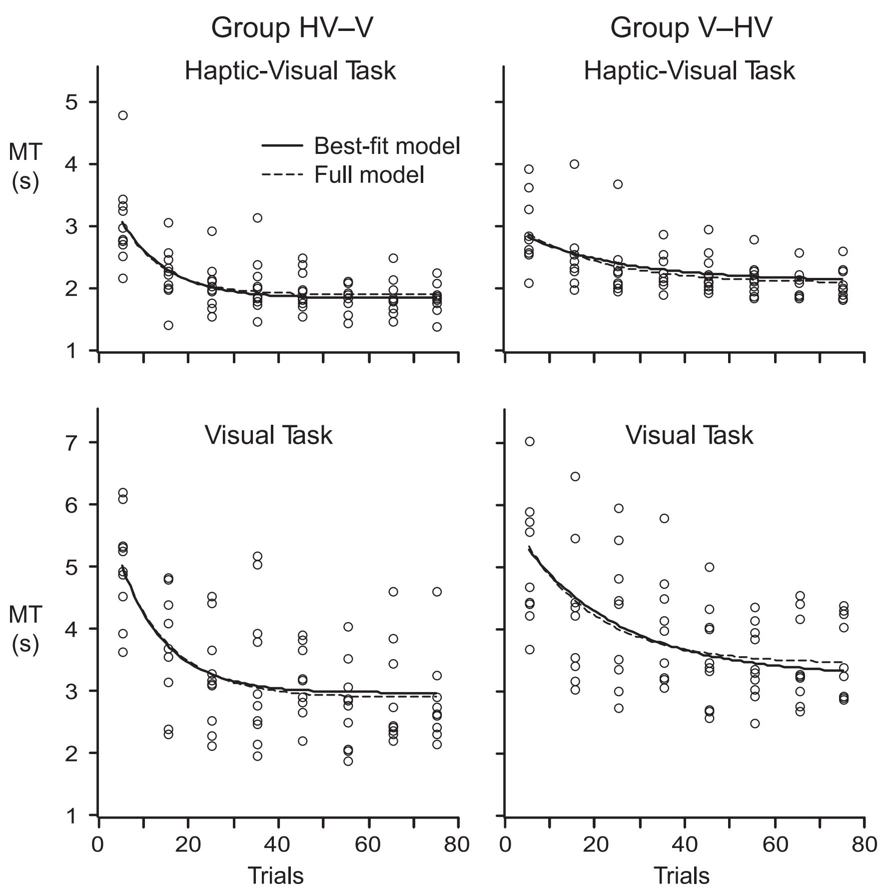

Fig. 2. Movement time (MT) as a function of trial block. Data are presented on separate panels for each group and experimental condition. Open circles represent individual participant means for each block of 10 trials. The dashed and solid lines correspond to exponential curve fits of the data using the full and best-fit models, respectively. HV, haptic plus vision; V, vision only.

$$MT = (a_0 + a_1T + a_2G)e^{(b_0+b_2G)block} + (c_0 + c_1T + c_2G)$$

(see MATERIALS AND METHODS). This exponential model revealed main effects of task ($P < 0.001$) and group ($P = 0.029$) on the leading value (a), main effects of task ($P < 0.001$) and group ($P = 0.035$) on the asymptote (c) of the exponential, and a main effect of group ($P = 0.010$) on the learning rate (b). There was no main effect of task on the learning rate and no interaction between task and group for any of the three parameters.

This best-fit model can be partitioned into the following four models for each combination of group and condition

$$\text{group HV} - \text{V, task HV: } MT = a_0e^{b_0x} + c_0 = 3.222e^{-0.963x} + 1.822$$

$$\text{group HV} - \text{V, task V: } MT = (a_0 + a_1)e^{b_0x} + (c_0 + c_1) = 5.321e^{-0.963x} + 2.947$$

$$\text{group V} - \text{HV, task HV: } MT = (a_0 + a_2)e^{(b_0+b_2)x} + (c_0 + c_2) = 1.104e^{-0.455x} + 2.104$$

$$\text{group V} - \text{HV, task V: } MT = (a_0 + a_1 + a_2)e^{(b_0+b_2)block} + (c_0 + c_1 + c_2) = 3.203e^{-0.455} + 3.229$$

These exponential fits are shown in Fig. 2, and for comparison, the figure shows the exponential fits for the full model (see MATERIALS AND METHODS). Consistent with the regression analysis, the additional parameters of the full model make little difference to the overall fit. In both cases, we found that final or asymptotic performance (i.e., MT at the end of learning) was significantly better in the HV task than in the V task and also that performance was significantly better for the HV-V group than for the V-HV group. A similar order effect was observed for the learning rate, which was approximately two times faster for the HV-V group than the V-HV group.

Consistent with the best-fit exponential model described above, repeated measures ANOVA revealed that for each combination of group and condition, MT decreased significantly from the first to the last block of 10 trials ($F_{1,\ 9} > 15.9$; $P < 0.003$ in all four cases). Across conditions and groups, mean MT dropped by 37% (see Figs. 3, *A* and *B*).

Two-way (task-by-group) ANOVA on MT during the first trial block (Fig. 3*C*) revealed a significant effect of task ($F_{1,\ 18} = 60.17$; $P < 0.001$) but no effect of group ($F_{1,\ 18} = 0.10$; $P = 0.75$) and no interaction ($F_{1,\ 18} = 0.98$; $P = 0.34$). Thus initial performance on either the HV or V task was not affected by previous experience with the other task. Concerning final performance, two-way ANOVA on the last trial block (Fig. 3*D*) showed a significant effect of task ($F_{1,\ 18} = 79.5$; $P < 0.001$). On average, MT was 63% longer when haptic feedback was absent (V task: M = 3.17 s) than when haptic feedback was present (HV task: M = 1.95 s). In addition, there was a significant effect of group ($F_{1,\ 18} = 6.71$; $P = 0.018$), demonstrating that prior experience influenced the ability of participants to manipulate the object. Specifically, the HV-V group, which started with full feedback, performed better overall (M = 2.33 s) than the V-HV group, which started with visual feedback only (M = 2.79 s). Finally, there was no task-by-group interaction, suggesting that starting with haptic feedback provided a final performance advantage in both tasks.

Trajectory analysis. Figure 4 shows two representative hand and object trajectories taken from the last 10 trials of the first session. That is, a participant in the HV-V group performed the trial from the HV task and a different participant in the V-HV group performed the trial from the V task. The figure shows the Y positions of the hand and mass (i.e., along the axis aligned with the start position and target), the Y distance between mass and object, and the Y velocities of the hand and mass. When haptic feedback was not available, the participant moved the

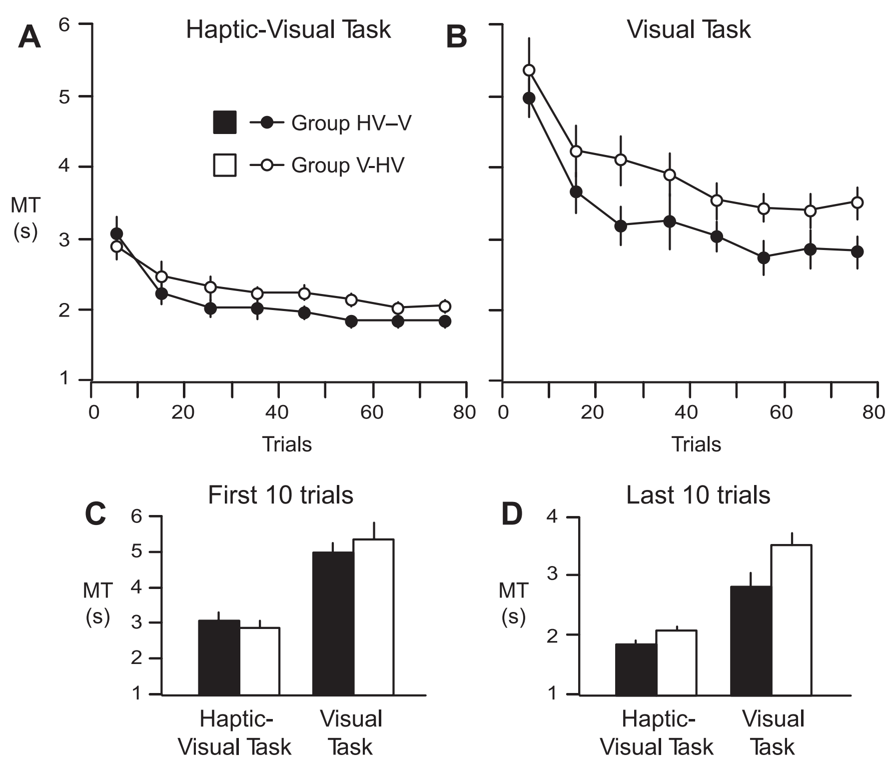

Fig. 3. Mean MT results. *A*: mean MT as a function of trial block and group in the HV task. *B*: same as *A* but for the V task. *A* and *B*: the white and black circles represent means averaged across participants in the V-HV and HV-V groups, respectively. *C*: mean MT in the first block of trials as a function of group and task. *D*: same as *C* but for the last block of trials. *C* and *D*: the white and black bars correspond to the V-HV and HV-V groups, respectively. For all panels, error bars correspond to the SE.

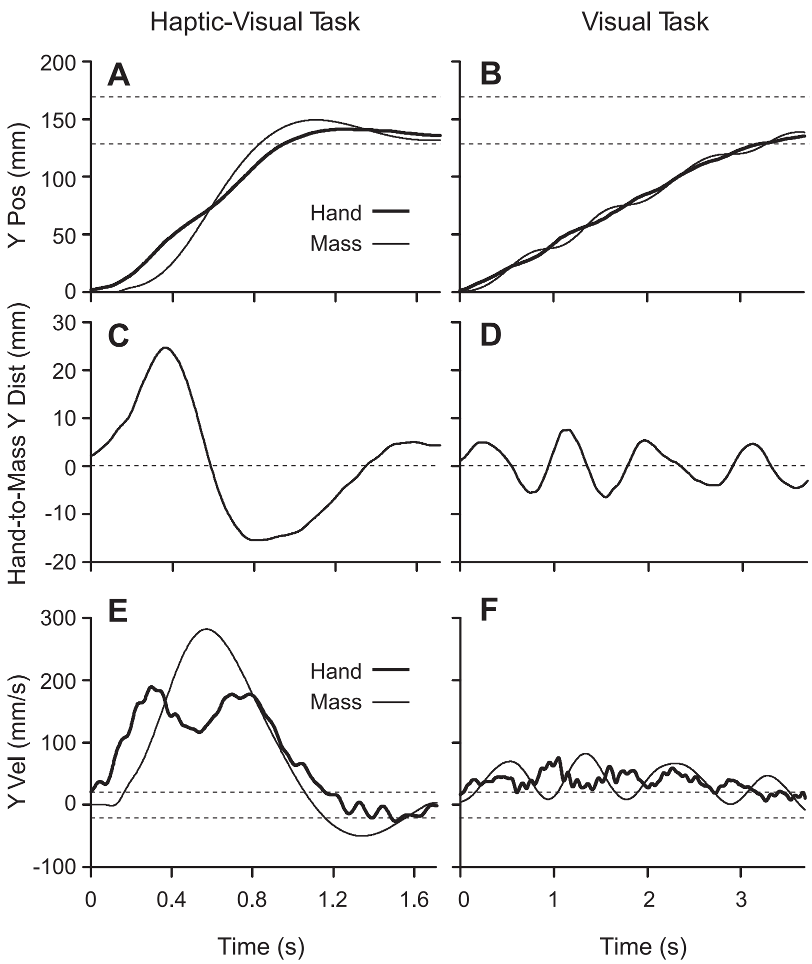

Fig. 4. Examples of representative trials in each task. *A* and *B*: hand and mass positions (Pos) along the *y* axis (main axis of movement) as a function of time. *C* and *D*: Y distance (Dist) between hand and mass as a function of time. *E* and *F*: hand and mass velocities (Vel) along the *y* axis as a function of time. *A*, *B*, *E*, *F*: thick and thin lines refer to hand and mass kinematics, respectively. Dashed lines represent criteria that were used to assess when a trial was completed successfully (see MATERIALS AND METHODS for further information). Each trial was performed by a different participant and was extracted from the last block of 10 trials. Note the different movement strategies used to displace the mass in the HV and V tasks.

hand slowly—making a series of submovements characterized by distinct hand velocity maxima (Fig. 4*F*)—and kept the mass close to the hand (Fig. 4*D*). In contrast, when haptic feedback was available, the participant moved the hand more quickly (Fig. 4*E*), and the trajectory of the object was quite different than that of the hand (Fig. 4*C*).

Figure 5 shows mean hand and object Y positions (Fig. 5, *A* and *B*) and the mean hand-to-mass Y distance (Fig. 5*C*) as a function of normalized time for each combination of task and group. These mean functions are based on participant means averaged over the last 10 trials. In both the HV and V tasks, the deviation between the hand and mass was greater for participants in the HV-V group compared with participants in the V-HV group. However, the difference between groups was far greater in the HV task than in the V task, revealing a strong effect of prior experience. Overall, the deviation between the hand and the mass was greater in the HV task, in which haptic feedback was provided, than in the V task. However, quite similar deviations were seen in the HV task performed by the V-HV group and the V task performed by the HV-V group (Fig. 5*C*), again revealing the strong effect of prior experience.

Figure 6 shows mean values of the average absolute Y distance between the hand and mass over the movement, as well as the number of crossings between the hand and mass Y positions. (As a reference, in Fig. 4, there are two and seven crossings for the trials shown for the HV and V tasks, respectively.) Repeated measures ANOVA revealed that for each task, both measures changed significantly across blocks of trials ($F_{7,\ 126} > 5.19$; $P < 0.001$). The average absolute distance between the hand and mass tended to increase across blocks in the HV task, whereas it tended to decrease across blocks in the V task. The number of crossings tended to decrease across blocks in both tasks.

Concerning final performance, two-way (task-by-group) ANOVA of the last trial block showed main effects of task ($F_{1,\ 18} = 11.2$; $P = 0.004$) and group ($F_{1,\ 18} = 11.8$; $P = 0.003$) on the average absolute distance between hand and mass (Fig. 7*A*). Although the effect of group was larger for the HV task, the interaction between task and group did not reach significance ($F_{1,\ 18} = 4.15$; $P = 0.056$). Thus in the first session, participants who received haptic feedback tended to allow the mass to move away from the hand, whereas participants who only received visual feedback tended to keep the mass closer to the hand. However, the effect of haptic feedback on the average absolute hand-to-mass distance was much smaller when considering the second session. The number of crossing was about two times greater in the V task compared with the HV task ($F_{1,\ 18} = 75.7$; $P < 0.001$; 5.6 vs. 2.5). There was also an effect of group ($F_{1,\ 18} = 7.48$; $P = 0.014$) and a significant task-by-group interaction ($F_{1,\ 18} = 7.09$; $P = 0.015$), due to the fact that the number of crossings was smaller for the HV-V group but only for the V task (corrected *t*-test; $P = 0.001$).

Grip–load force coupling. To examine the coupling of grip force and load force in the HV task, in which substantial load

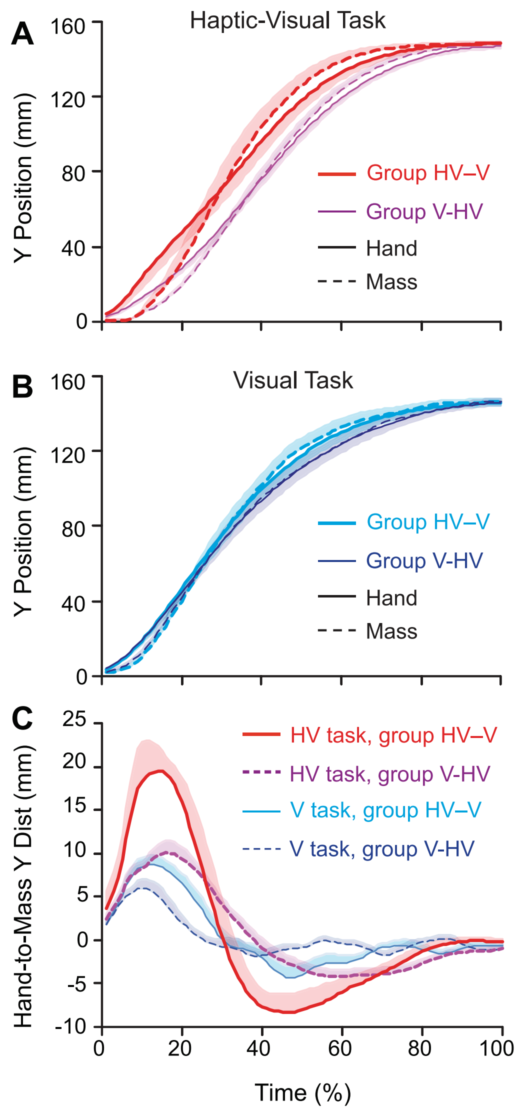

Fig. 5. Mean trajectories in the last block of trials. *A*: mean hand (solid lines) and mass (dashed lines) positions as a function of normalized time for each group in the HV task. *B*: same as *A* but for the V task. *C*: mean hand-to-mass distance as a function of normalized time for each group and task. For all panels, the mean trajectories are based on participant means averaged over the last 10 trials. Prior to averaging, trials were normalized with respect to MT. Shaded areas correspond to 1 SE.

forces acted on the object, we computed the coefficient of correlation between grip force and load force for each trial. Figure 8 shows mean correlation coefficients, averaged across participant means, as a function of trial block for each group. A two-way (trial block-by-group) ANOVA revealed significant effects of trial block ($F_{7,\ 126}$ = 4.14; $P < 0.001$) and group ($F_{1,\ 18}$ = 5.01; P = 0.04). The coupling between grip force and load force tended to increase with trial block and was consistently greater when haptic feedback was provided in the first session (HV-V group; R = 0.66) than when it was provided in the second session (V-HV group; R = 0.46). We also determined the maximum load force in each trial of the HV task. A two-way (trial block-by-group) ANOVA revealed that the maximum load force increased across blocks ($F_{7,\ 126}$ = 2.06; P = 0.05) and was greater for the HV-V group than the V-HV group (2.9 vs. 1.1 N; $F_{1,\ 18} > 10.48$; P = 0.005). These effects are consistent with earlier observations showing that MT was lower in the HV-V group than the V-HV group and that MT decreased across trials blocks.

DISCUSSION

The current study yielded several key findings. First, in agreement with earlier studies, in which haptic feedback was provided (Dingwell et al. 2002, 2004; Nagengast et al. 2009), we found that people could improve their ability to control the movement of a nonrigid object. Second, improvements in control also occurred in the absence of appropriate haptic feedback, arising from interaction forces between the hand and object. Third, haptic feedback allowed greater dexterity in manipulating nonrigid objects as measured by MTs. Fourth, previous experience influenced the way participants manipulated the nonrigid object. Although positive transfer was found when appropriate haptic feedback was removed, quite unexpectedly, negative transfer was found when appropriate haptic feedback was added. Fifth, we found that participants appeared to use distinct control strategies when moving the object with and without haptic feedback. With haptic feedback, considerable stretching of the spring, linking the hand and mass, was found in naïve participants. In contrast, without haptic feedback, the mass was kept close to the hand in naïve participants. Finally, we found that in the haptic version of the task, the coupling between grip force and load force improved across trials, suggesting that participants acquired an increasingly accurate representation of the interaction forces between the hand and mass.

Contributions of haptic and visual feedback. On the one hand, one might expect haptic feedback related to interaction forces to improve control, because such feedback should allow more accurate sensory estimates of the state of the object through multisensory integration (Ernst and Banks 2002; Ernst and Bülthoff 2004; van Beers et al. 2002). On the other hand, because interaction forces perturb the hand, one might expect haptic feedback to degrade control (Dingwell et al. 2002; Huang et al. 2006). Although previous experiments have examined the contributions of haptic and visual feedback in performing skilled object manipulation tasks (e.g., Sternad et al. 2001), to our knowledge, only one study has addressed this issue explicitly in the context of learning to manipulate a nonrigid object. As mentioned in the introduction, Huang and colleagues (2006), who examined a task in which participants had to control the position of a ball on a beam, found virtually no benefit of haptic information; participants who received appropriate haptic feedback began and finished their training session with comparable performance with participants who received visual feedback only (see Table 3 in Huang et al. 2006). In contrast, we found that haptic feedback facilitates both initial and final performance in naïve participants. In the absence of haptic feedback, initial and final MTs increased by 75% and 92%, respectively, and the number of crossings between the hand and mass increased by 260%. This comparison between these two studies suggests that the contribution of haptic information to the manipulation of objects with complex dynamics can vary substantially depending on the properties of the object and task. However, our observation that haptic feedback is helpful when manipulating a mass-spring system is consistent with another study by Huang and colleagues (2007),

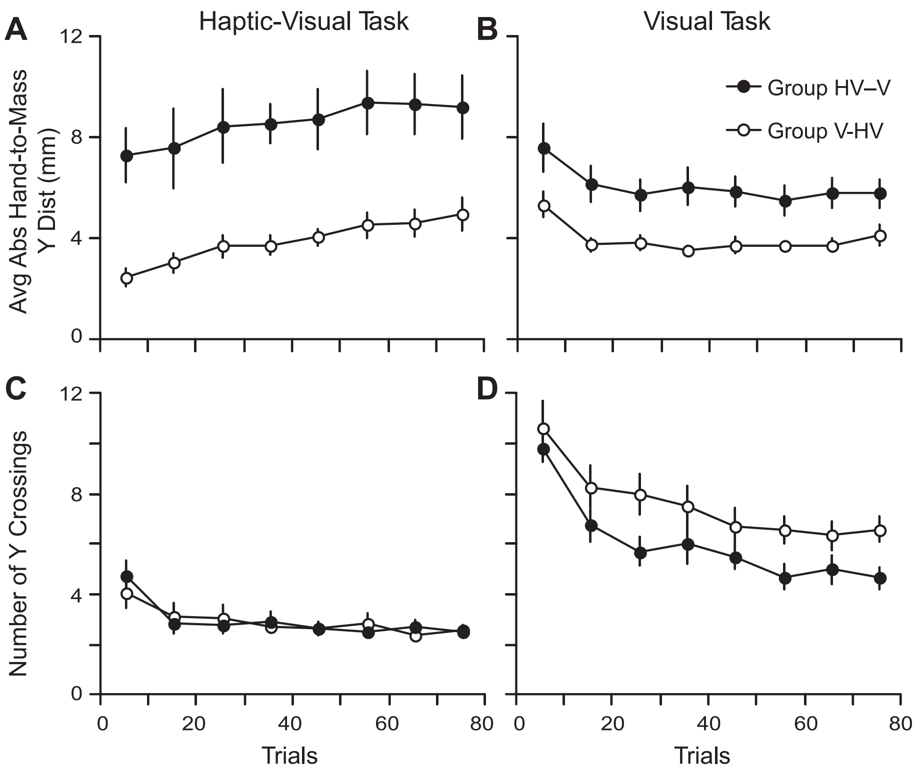

Fig. 6. Means of kinematic variables. *A*: average absolute (Avg Abs) hand-to-mass distance in the HV task as a function of trial block and group. *B*: same as *A* but for the V task. *C* and *D*: same as *A* and *B* but for the number of crossings between hand and mass along the *y* axis. In all 4 panels, black and white circles correspond to the HV-V and V-HV groups, respectively. Error bars correspond to 1 SE.

in which they examined the ability to oscillate and tune a mass-spring system at its resonance frequency. Future work will be required to determine which aspects and/or features of a mass-spring system make haptic feedback beneficial.

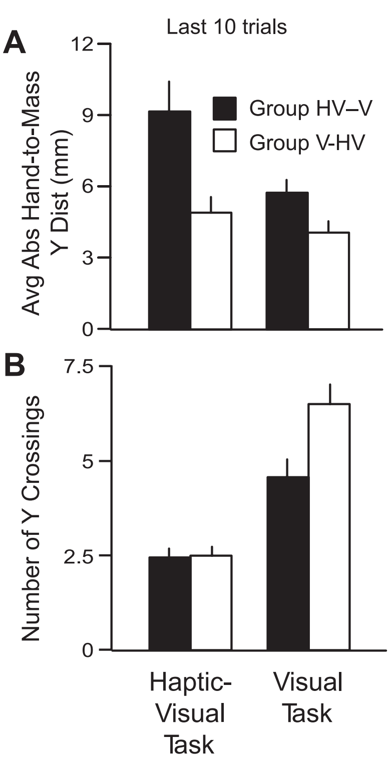

Fig. 7. Means of kinematic variables in the last trial block. *A*: average hand-to-mass distance in the HV task as a function of task and group. *B*: same as *A* but for the number of crossings between and mass along the *y* axis. For all panels, black bars correspond to the HV-V group, and white bars correspond to the V-HV group. Error bars correspond to 1 SE.

Although we found that haptic feedback improved performance, our participants were still able to complete the task and improve performance across trials when only visual feedback was provided. Overall, participants in the V task reduced their MT by ~40% between the first and the last block of trials—a reduction that was similar to that observed in the HV task. The fact that participants could control the mass-spring system based solely on visual information extends earlier observations made in the context of bouncing a ball on a racket (Sternad et al. 2001) or balancing an inverted pole (Mehta and Schaal 2002).

Learning internal models of nonrigid objects. It has been argued that learning to control a nonrigid mass-spring object involves the acquisition of an internal model of the object's dynamics (Dingwell et al. 2004). Internal models of object dynamics capture the mapping between the force applied to the

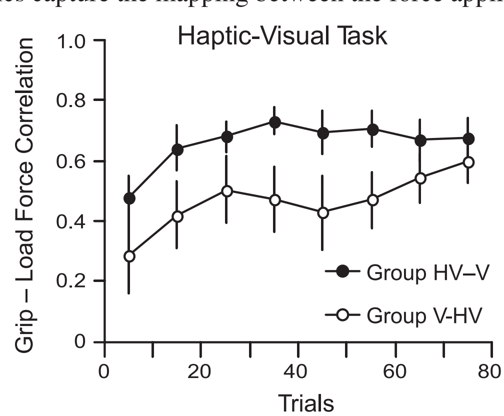

Fig. 8. Grip–load force coupling in the HV task. Average correlation coefficients of the correlation between grip force and load force as a function of trial block for both the HV-V (black circles) and V-HV (white circles) groups. Each point represents the mean of participants averaged across trials within the block. Error bars correspond to 1 SE.

object and the motion of the object (or the mapping between arm motor commands and object motion). Such models enable the sensorimotor system to predict the consequences of motor commands, in which case, they are referred to as forward models (Wolpert and Flanagan 2001; Wolpert and Ghahramani 2000). Our results pertaining to the coupling between grip and load force support the idea that participants learned a forward model of the mass-spring system. To assess participants' ability to predict dynamics of the mass-spring system in the HV task, we measured the correlation between grip force and load force (Danion and Sarlegna 2007; Flanagan and Wing 1997). We found that correlation coefficients (R values) were initially low but increased substantially over the first three blocks of trials. Interestingly, roughly parallel changes were observed in MT, which decreased substantially over the first three blocks (Fig. 3*A*). Indeed, across trial blocks in the HV task, the correlation between mean R values and mean MT was -0.96 ($P < 0.001$). The rather gradual improvement in grip–load coupling observed in the current study may be contrasted with the rapid adaptation of grip forces reported for a task in which participants grasped and moved a rigid object with an unfamiliar load (Flanagan et al. 2003).

Transfer between tasks: internal models and movement strategies. One aim of our study was to determine how learning to control a nonrigid object without haptic feedback influences control when haptic feedback is provided and vice versa. Our results provide clear evidence that previous experience in one version of the task influenced the ability to perform the other version of the task. However, those transfer effects were not symmetrical. Although earlier practice with haptic feedback improved the ability to perform the task without haptic feedback, earlier practice without haptic feedback was detrimental to performing the task with haptic feedback. As noted above, there is evidence that learning to control a nonrigid object involves acquiring an internal model of the object's dynamics. We reasoned that if participants learned a direct mapping between arm motor commands and object motion, then because this mapping depends on whether interaction forces between the hand and object are present, negative transfer should occur between the HV task and the V task and vice versa. Alternatively, we proposed that in principle, participants could learn two mappings: the mapping between motion of the hand and motion of the mass (i.e., between the states of the hand and mass) and the mapping between arm motor commands and hand motion. If so, it is not clear whether transfer would be positive or negative. On the one hand, because the former mapping is independent of interaction forces and is the same in both tasks, we might have expected positive transfer between the HV and V tasks in both directions. On the other hand, because the latter mapping changes between tasks, negative transfer might be expected between the HV and V tasks in both directions. However, none of these scenarios was supported, because negative transfer from the V task to the HV task was observed, whereas positive transfer occurred from the HV task to the V task.

Asymmetric transfer of learning could arise if participants adapted their arm motor commands to interaction forces more slowly than they de-adapted their arm motor commands when interaction forces were removed (Davidson and Wolpert 2004; Shadmehr et al. 1998; Smith et al. 2006). However, although this scheme predicts that transfer of learning from the V task to the VH task will be poorer than the transfer in the opposite direction, it does not predict whether the transfer will be positive or negative. Based on the above considerations, it seems difficult to explain the asymmetric transfer effects we obtained in the context of learning mappings or internal models.

As an alternative, we suggest that the asymmetric effects of previous experience can be understood in the context of control strategies, namely the process of optimizing/selecting movement trajectories, which is distinct from learning dynamics. We observed that the hand-to-mass distance varied substantially depending on the experimental conditions. In the HV task, naïve participants allowed the mass to move quite far away from the hand. This resulted in movements characterized by a relatively low number of hand velocity peaks and crossings between the hand and mass. In contrast, in the V task, naive participants kept the mass close to the hand, which resulted in movements featuring a large number of hand velocity peaks and crossings between the hand and mass. Altogether, it seems that in the HV task, naïve participants learned to control the degrees of freedom associated with the mass, whereas in the V task, naïve participants tended to do the opposite and froze the mass. Thus naïve participants used what might be referred to as a lead-lag strategy when haptic feedback was provided and a dragging strategy when haptic feedback was not available. The main advantage of the lead-lag strategy is that it allows faster hand movements. However, this strategy requires the ability to quickly damp the resulting oscillations of the mass. In contrast, the dragging strategy does not allow fast hand movements, but the ability to damp terminal oscillations is less crucial, since these oscillations are likely to be small. Last but not least, visual feedback processing is relatively slow compared with somatosensory feedback control (200 vs. 80 ms), and this may have contributed to slower hand movements in the V task.

Our results indicate that when the two groups of participants exchanged tasks, they did not fully exchange strategies. Instead, they tended to stick, at least partially, with their initial strategy. As a consequence, both groups ended up adopting a rather similar, intermediate strategy. In other words, when participants had prior experience with haptic feedback, they allowed the mass to move more freely in the V task than naïve participants. Conversely, when participants had prior experience in the V task, they were reluctant to free the mass in the HV task, compared with naïve participants. Because fast completion times are possible only if the mass is moved away from the hand, this carryover effect (i.e., tendency to stick with the initial strategy) was beneficial to participants who started with haptic feedback, whereas it was detrimental to those who started without.

Implications for training in VR simulators. Our finding that haptic feedback as well as prior experience with haptic feedback enhance the ability to control a nonrigid object has implications for the design of teleoperation devices and VR simulators, such as those used in surgical training. This is particularly obvious for surgical simulators, because trainees will use these devices to learn how to handle a wide variety of soft tissues (Basafa and Farahmand 2010; Lim et al. 2009). A typical issue when designing VR simulators is whether the provision of haptic feedback, which can be both difficult and costly, is necessary or justified. In line with our results, a number of studies have found that haptic feedback enhances performance in surgical simulator training (Panait et al. 2009; Ström et al. 2006; van der Meijden and Schijven 2009). However, a novel finding brought by our study is that training without haptic feedback (i.e., with V) can lead to persisting detrimental effects if operators subsequently have to work with haptic feedback. This would typically be the case, when after simulated training, operators would then have to perform the real task.

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DISCLOSURES

No conflicts of interest, financial or otherwise, are declared by the author(s).

AUTHOR CONTRIBUTIONS

Author contributions: F.D. and J.R.F. conception and design of research; J.S.D. performed experiments; F.D. and J.R.F. analyzed data; F.D. and J.R.F. interpreted results of experiments; F.D. and J.R.F. prepared figures; F.D. and J.R.F. drafted manuscript; F.D. and J.R.F. edited and revised manuscript; F.D. and J.R.F. approved final version of manuscript.

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