Haptic Feedback Enhances Force Skill Learning

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Abstract

This paper explores the use of haptic feedback to teach an abstract motor skill that requires recalling a sequence of forces. Participants are guided along a trajectory and are asked to learn a sequence of one-dimensional forces via three paradigms: haptic training, visual training, or combined visuohaptic training. The extent of learning is measured by accuracy of force recall. We find that recall following visuohaptic training is significantly more accurate than recall following visual or haptic training alone, although haptic training alone is inferior to visual training alone. This suggests that in conjunction with visual feedback, haptic training may be an effective tool for teaching sensorimotor skills that have a force-sensitive component to them, such as surgery. We also present a dynamic programming paradigm to align and compare spatiotemporal haptic trajectories.

1. Introduction and Related Work

Haptic feedback has become an integral component of numerous simulation systems, particularly systems designed for teaching surgical skills (e.g. [3],[9],[19]). Haptic rendering in nearly all such simulation environments has been designed to realistically replicate the real-world forces relevant to a particular task. Recent results suggest that simulation environments can contribute to users' learning of real motor skills [22] and to users' perception of virtual object shapes [8]. In contrast, Adams et al [1] found no significant learning benefit from haptic feedback for a manual assembly task, despite an overall benefit from training in a virtual environment.

Although haptic feedback is often used to replicate real-world interaction forces, haptics has the potential to provide cues that are not available in the physical world. In particular, haptic feedback can be used as a channel for presenting motor patterns that a user is expected to internalize and later recall. Feygin et al [5] referred to this approach as "haptic guidance", and found that haptic feedback contributes to learning spatiotemporal trajectories. Williams et al [20] employed this technique in a medical simulator and also found that it contributed to learning position trajectories. Patton and Mussa-Ivaldi [13] employed an implicit version of this technique, allowing users to adapt to a movement perturbation in order to teach a contrary motion. In contrast, Gillespie et al [6] used a similar approach to teach a motor control skill, and found no significant benefit from haptic training, although haptic training did affect the strategy that participants used when performing the motor skill in the real world. Huang et al [7] required participants to excite a virtual oscillator with visual, haptic, or visuohaptic feedback, and found visuohaptic feedback to be superior to the other modalities (consistent with the results presented here for a significantly different task). O'Malley et al [12] found that using haptic constraints provides significant benefit for both performing and learning movement patterns.

However, little work to date has demonstrated the ability of haptic feedback to teach a precise sequence of *forces* that should be applied as a user moves along a trajectory in space. This type of learning is relevant to force-sensitive, visually-guided tasks, particularly including numerous surgical procedures ([17],[18]). Yokokohji et al [21] presented forces contrary to a correct level of force for an object-manipulation task, but found that this approach was ineffective for the task they were evaluating. More recently, Srimathveeravalli and Thenkurussi [16] used haptic feedback to teach users to replicate both shape and force patterns, but found insignificant benefit of haptic feedback for learning shape patterns, and did not find haptic training to be beneficial at all for learning force patterns.

The present work examines a task in which the participants' goal was to learn and recall a pattern of forces along a single axis while moving along a planar curve. In this context, we demonstrate that haptic feedback is beneficial for learning a series of forces along a movement trajectory.

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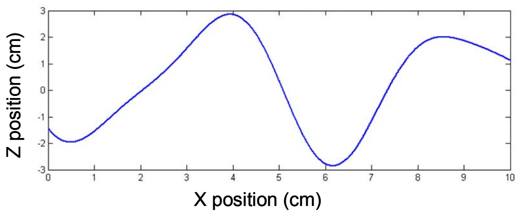

Figure 1. A typical experimental spatial trajectory.

2. Methods

We describe an experiment that assesses the impact of haptic feedback on participants' ability to learn a sequence of forces. Participants were presented with sequences of forces via three training modalities – visual, haptic, and combined visuohaptic – and were asked to recall those forces. While learning and recalling forces, participants were passively moved along a spatial trajectory, which was also presented visually. The participants used this trajectory as position references for force patterns. A more detailed description of this experiment follows.

2.1 Participants

Twelve right-handed participants, nine male and three female, aged 19 to 21, took part in the present study. All were undergraduate students. None had previous experience with haptic devices. Participants were compensated with a $5 gift certificate, and an additional $10 gift certificate was offered to the three participants with the highest overall score (across all conditions) as incentive. Written consent was obtained from all participants; the consent form was approved by the Stanford University Institutional Review Board.

2.2 Apparatus

Visual information was presented on a 19" LCD monitor placed approximately 2.5' from the user. Haptic feedback was presented via an Omega 3-DOF force-feedback device (Force Dimension, Lausanne, Switzerland), resting on a table in front of the monitor. This device was selected because it was able to deliver the sustained forces required for this experiment (up to 8N for up to twenty seconds), which other commercially-available haptic devices could not. Participants were able to rest their elbow on a table. Software was run on a dual-CPU 2GHz Pentium 4 computer running Windows XP, and was developed in C++ using the CHAI toolkit [4]. The software used for this experiment has been made available online; see Appendix A for download information.

2.3 Stimuli

The following axis convention was used in the present study:

- The *x* axis runs from the participant's left to the participant's right (parallel to the table)
- The *y* axis runs upward (perpendicular to the table)
- The *z* axis runs toward the user (in and out of the display plane)

Spatial trajectories were generated for each trial to passively move the participant's hand from left to right while sinusoidally varying the participant's hand position along the z axis. The spatial trajectory had no y component; i.e. it was entirely in a plane parallel to the table. Trajectories spanned 10cm in the horizontal (*x*) direction and 6cm in the z direction, and moved the user at a constant velocity of 1.6cm/s. The *z* component of each trajectory was the sum of twenty sinusoids with random frequencies, phases, and DC offsets, with a maximum spatial frequency of 0.3 cycles per centimeter. After summing the sinusoids, each trajectory was scaled to fit the 6cm range in z. A typical spatial trajectory is presented in Figure 1.

Force patterns were generated for each trial along the y axis, perpendicular to the plane of movement along the spatial trajectory. These patterns are the values that the participant was asked to learn in each trial. Force patterns were generated as functions of time, but because the participant was moved along the trajectory at a constant rate, force patterns were also fixed relative to the spatial trajectory. The temporal force patterns were generated as the sum of four sinusoids with random frequencies, phases, and DC offsets, with a maximum frequency of 0.2Hz. After sinusoidal summing, force patterns were scaled into the range [0N,10N]. To introduce limited higher-frequency peaks without creating unreasonably jagged force patterns, parabolic "bumps" were randomly blended into each sinusoidal trajectory; these bumps were allowed to range up to 12N. After summing the base pattern and the parabolic bumps, the final force pattern was ramped up and down over the first and last one second of the pattern to avoid jerking the haptic device. A typical force pattern is presented in Figure 2. This graph represents the *magnitude* of the normal force the participant was asked to learn; the learned force was in all cases in the downward (–y) direction.

2.4 Experimental Conditions

The following 3 training conditions were employed in a blocked design: haptic display of normal force (H), visual display of normal force (V), and combined visuohaptic display of normal force (VH). In all three conditions, the participant's hand was pulled along the spatial trajectory (in the *xz* plane) via a proportional-derivative (PD) controller with proportional and

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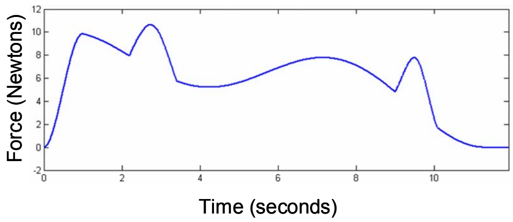

Figure 2. A typical experimental force pattern.

derivative gains of 0.9N/mm and 0.1N·s/mm, respectively. Offline analysis showed no significant lag behind the ideal trajectory in any participant's data, indicating that the gain was sufficiently high. The visual display showed the spatial trajectory, along with a display of the participant's current device position, under all three training conditions.

In the haptic (H) training condition, the haptic device applied the *opposite* of the embedded force pattern directly to the user along the $+y$ direction (perpendicular to the movement plane). The participant was instructed to keep the device in the movement plane, i.e. to precisely oppose the upward force applied by the device. In this manner, the participant practiced applying the sequence of forces that he/she was expected to learn. Figure 3a shows the display presented to the user in the H condition.

In the visual (V) training condition, the haptic device was constrained to the xz plane by a PD controller with P/D gains of 2.0N/mm and 0.3N·s/mm, respectively. No haptic representation of the embedded force pattern was presented. As the user was pulled along the trajectory, an on-screen vertical bar changed its height to indicate the magnitude of the target normal force at the current trajectory position. This bar moved along the trajectory along with the representation of the participant's current device position, so the participant could visually attend to both simultaneously. Figure 3b shows the display presented to the user in the V condition.

In the combined visuohaptic (VH) training condition, the haptic device was constrained to the xz plane as in the visual (V) condition, and the current target force is displayed as a blue bar, as in the visual condition. However, an additional graphical bar is presented in green. The additional bar indicates the normal force currently being applied by the participant. Participants were instructed to match the heights of the blue and green bars. Thus the participants were – via the plane constraint – receiving haptic feedback equal to the target force pattern. Figure 3c shows the display presented to the user in the VH condition.

A fourth condition – the test (T) condition – was used following all training conditions to evaluate learning through force recall. The visual display in this condition was identical to that used in the haptic (H) condition; no visual indication of force was provided. In the test condition, the haptic device was constrained to the xz plane as in the visual (V) condition. The user was instructed to apply the learned pattern of forces in the y direction (normal to the spatial trajectory).

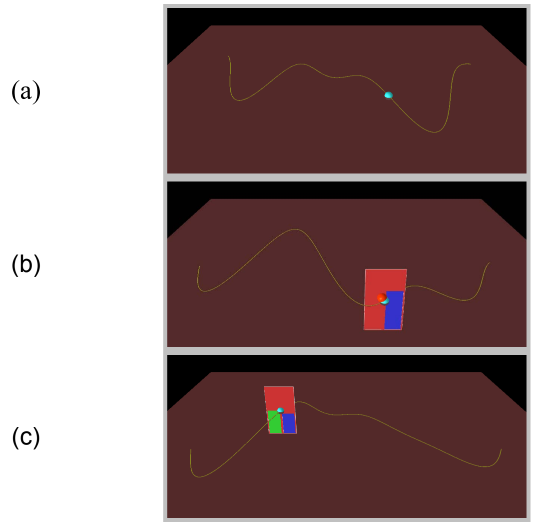

Figure 3. The visual representations of the spatial trajectory and normal force presented to the user in the (a) haptic training condition (no visual representation of force), (b) visual training condition (blue bar representing current target force), and (c) combined visuohaptic training condition (blue bar representing current target force magnitude and green bar current user-applied force magnitude).

In all three training conditions, a small square appeared on screen when the device reached saturation; this was added to be "fair" to the visual training condition, which otherwise did not provide any indication of absolute force magnitude.

2.5 Experimental Procedure

Each participant was given an introduction to each of the conditions described above, and was then asked to participate in 72 trials, with a ten-minute break after 36 trials to prevent fatigue. A trial consisted of a single training/testing pair. For each trial, the participant was presented with a trajectory using one of three training conditions (H, V, VH) and was immediately tested on that trajectory using the test (T) condition described above. Trials were grouped into blocks of three training/testing pairs that repeated the *same* trajectory and *same* force profile using the *same* training condition.

For example, for a V condition trial block, the participant was trained with the visual bargraph display of force by traversing the trajectory from left to right once. After returning the stylus tip position to the left

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of the trajectory, the participant was immediately tested for force recall once (thus completing one trial). This training/testing pair was then repeated twice more (for a total of three trials per block). A new training condition was then randomly selected, and a new trajectory and a new force profile were randomly generated, for the next trial block.

In summary, each participant completed a total of 72 trials, representing 24 trial blocks for each of the H, V and VH conditions. Throughout the experiment, the device positions and applied normal forces were recorded to disk for offline analysis.

3. Data Analysis

Each testing trial is scored individually for accuracy of force recall. The input to the scoring mechanism is two force-vs-time curves: the "target" force pattern and the "applied" force pattern. If these curves are similar, the trial should receive a high recall accuracy score. A simple scoring approach might simply subtract the two curves and compute the root-mean-squared (RMS) difference at each point. The synthetic example shown in Figure 4 illustrates why this is an inadequate approach. In this figure, the black line represents a synthetic "correct" force pattern with three clear peaks. The red line represents the force pattern recorded from a hypothetical user who correctly recalled the three force peaks, each with a slight timing error. The green line represents the force pattern recorded from a hypothetical user who did not apply any force at all. A simple RMS-difference approach to scoring would assign a significantly lower score to the red curve than to the green curve, even though the red curve represents a significantly more accurate recall. Feygin et al [5] computed an optimal linear transformation (scale and shift) to correct for similar errors. This approach, however, will not adequately align all three peaks in this example, because the three peaks are offset in different directions. In other words, different regions of the curve are scaled differently. This

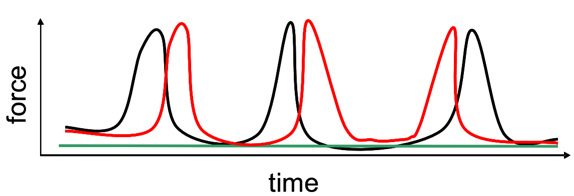

Figure 4. A synthetic example illustrating the need for non-affine trajectory alignment. The black line represents a synthetic "correct" force pattern. The red line represents the force pattern recorded from a hypothetical user who correctly recalled the three force peaks, and the green line represents the force pattern recorded from a hypothetical user who didn't apply any force at all.

problem is even more significant in real data series, which are more complex than this synthetic example.

To address this problem and properly assess recall accuracy in a manner that is robust to local timing errors, we employed a scoring scheme based on dynamic programming (DP). This approach has often been employed to align curves for shape recognition ([2],[11],[14]) and speech recognition [15], and a similar approach was used by Patton and Mussa-Ivaldi [13] for matching "haptic attributes". We describe our adaptation of dynamic programming for aligning force-vs-time curves.

For each trial, the target and applied force patterns are resampled to a common time base, and the applied force patterns are low-pass filtered by a box filter with a width of 100 milliseconds. An error matrix is then constructed to describe how well each point on the target pattern "matches" each point on the applied pattern. If the resampled trajectories are 1000 samples long, this matrix contains 1000^2 entries. The entry at location (i,j) answers the question: "how similar is point i in the target force pattern to point j in the applied force pattern?" For this experiment, each entry in the error matrix is a weighted sum of the RMS difference in forces and the RMS difference in slopes (df/dt values) between the two points being compared. A penalty value is also specified to the dynamic programming algorithm to penalize time distortions. Dynamic programming is then used to find an optimal (minimum-cost) pairing between samples on the target and applied curves. Figure 5 shows the alignment suggested by dynamic programming for a single trial.

The applied force pattern is warped, according to this alignment, to the same time base as the target force pattern. Figure 6 shows the same trial after warping the applied force pattern according to the DP result.

After DP and warping, a score is assigned to each trial as a weighted average of the DP alignment cost, the RMS difference between the two curves after warping, and the RMS difference between the two curves' slopes after warping. Weights were adjusted empirically to match visual assessments of recall accuracy without knowledge of the experimental conditions for each of the assessed trials. These weighted scores are used to assess the quality of recall for each trial. A score of 0 indicates perfect recall; larger scores indicate lower recall accuracy.

4. Results

Scores are pooled over each training condition, allowing us to compare the recall quality for each training condition (864 recall trials per condition). A one-way ANOVA confirms a significant difference among the three training paradigms (F(2,862)=10.61,

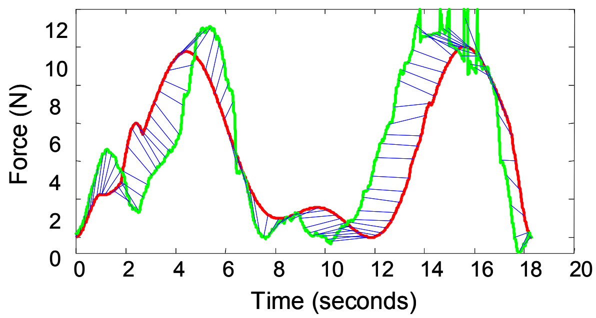

Figure 5. The alignment computed by dynamic programming for a single trial. The red curve is the target force pattern, the green curve is the applied force pattern, and the blue lines connect points on each curve that are aligned by dynamic programming.

$p<0.001$). Figure 7 shows the mean recall error for each training paradigm with 95% confidence intervals. Two-tailed T-tests with correction for multiple comparisons show that visual training promotes significantly more accurate recall than haptic training ($p=0.02$), visuohaptic training promotes significantly better recall than visual training ($p=0.007$), and visuohaptic training promotes significantly better recall than haptic training ($p<0.001$).

Table I presents the paradigms that promoted the most and least accurate recall for each participant. We observe that 9 of 12 participants had the lowest mean error in the visuohaptic training mode, and only 1 of 12 participants had the highest mean error in the visuohaptic training mode. This is consistent with the results presented in Figure 7, indicating again that visuohaptic training is the most effective paradigm.

5. Discussion and Conclusion

The results presented here demonstrate that participants are better able to memorize instructed force patterns when those patterns are presented both visually and haptically, rather than via either modality alone. This is in contrast to the result presented by Srimathveeravalli and Thenkurussi [16], who asked participants to replicate a force pattern and a position trajectory simultaneously. Their results show that including force information in a skill training paradigm produced *lower* overall error in participants' recall of *positional* information, but *higher* overall error in the participants' recall of *forces*. However, the task they were exploring was significantly more complex: users were asked to recall both force and position in multiple degrees of freedom. Our experiment focused on force alone – with position provided passively as a reference – and only focused on a single axis of force. This more focused task is likely the basis for the difference in results. Additionally, their experiment used smaller movements and a device with lower dynamic range, which may have limited participants' ability to recall force information.

Our results also show that haptic training alone is significantly less effective for this task than visual training alone. This is somewhat surprising, since the task is a force-specific task and visual feedback lacks absolute magnitude information. It is likely that the novelty of memorizing information presented haptically was a confounding factor; visual learning is so pervasive in everyday life that our results may understate the relative potential for learning via haptics alone. Future experiments will explore the use of haptic information alone to improve training.

The effectiveness of combined visuohaptic training suggests that haptic training may play an important role in teaching skills like surgery, which are visually-guided but often require different normal and tangential forces to be applied at different places in the workspace. The results presented here suggest a role not only for the use of haptic simulation incorporating simulated environmental feedback, but also active presentation of "correct" forces in a surgical context.

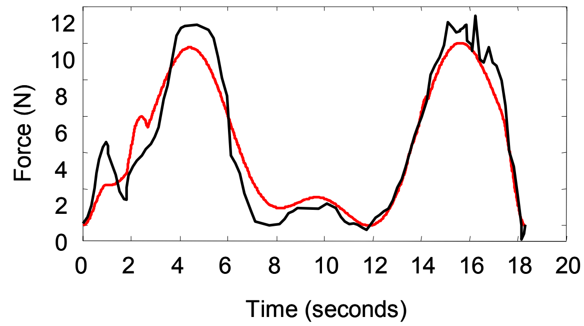

Figure 6. The target (red) and applied (black) forces for a single trial after warping the applied forces according to the results of dynamic programming (see illustration in Figure 5).

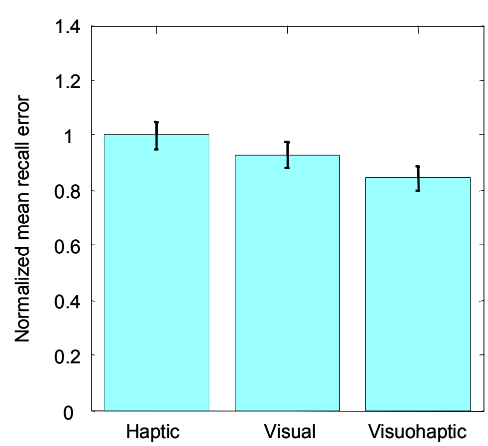

Figure 7. Mean recall error (in relative units) for each training paradigm. Error bars indicate 95% confidence intervals.

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Participant	Best paradigm	Worst paradigm
1	**Visuohaptic**	Visual
2	**Visuohaptic**	Haptic
3	Visual	Haptic
4	**Visuohaptic**	Visual
5	**Visuohaptic**	Haptic
6	Visual	**Visuohaptic**
7	**Visuohaptic**	Haptic
8	Haptic	Visual
9	**Visuohaptic**	Haptic
10	**Visuohaptic**	Haptic
11	**Visuohaptic**	Haptic
12	**Visuohaptic**	Haptic

Table 1. Training paradigms promoting the most and least accurate mean recall for each participant.

These forces may come from online interaction with an experienced instructor, a paradigm we refer to as "haptic mentoring", or from playback of prerecorded forces. Toward this end, we have incorporated the approach presented here into a surgical simulation system [10], and future work will include evaluation of the user's ability to transfer force-sensitive skills from the simulator to the real environment.

Additionally, we plan to conduct further experiments to explore the roles played by visual and haptic information in the combined visuohaptic training paradigm. This study was designed to evaluate the overall effectiveness of each paradigm in training force patterns, but additional experiments may allow us to identify whether certain frequency components of the target force patterns are being conveyed through one modality or the other.

Appendix A: Software Availability

The software used to conduct this experiment is available, along with data-manipulation scripts, at http://cs.stanford.edu/~dmorris/haptic_training .

Acknowledgements

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