Published in final edited form as:

IEEE Trans Haptics. 2012 ; 5(4): 356–364. doi:10.1109/ToH.2011.52.

Learning Kinematic Constraints in Laparoscopic Surgery

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Abstract

To better understand how kinematic variables impact learning in surgical training, we devised an interactive environment for simulated laparoscopic maneuvers, using either 1) mechanical constraints typical of a surgical “box-trainer” or 2) virtual constraints in which free hand movements control virtual tool motion. During training, the virtual tool responded to the absolute position in space (Position-Based) or the orientation (Orientation-Based) of a hand-held sensor. Volunteers were further assigned to different sequences of target distances (Near-Far-Near or Far-Near-Far). Training with the Orientation-Based constraint enabled much lower path error and shorter movement times during training, which suggests that tool motion that simply mirrors joint motion is easier to learn. When evaluated in physically constrained (physical box-trainer) conditions, each group exhibited improved performance from training. However, Position-Based training enabled greater reductions in movement error relative to Orientation-Based (mean difference: 14.0 percent; CI: 0.7, 28.6). Furthermore, the Near-Far-Near schedule allowed a greater decrease in task time relative to the Far-Near-Far sequence (mean –13.5 percent, CI: –19.5, –7.5). Training that focused on shallow tool insertion (near targets) might promote more efficient movement strategies by emphasizing the curvature of tool motion. In addition, our findings suggest that an understanding of absolute tool position is critical to coping with mechanical interactions between the tool and trocar.

Index Terms

Laparoscopic surgery; motor learning; kinematic constraints

1 Introduction

Bench-Top box trainers have served as valuable tools for the challenging and prevalent problem of teaching surgical laparoscopic skills [1], [2], [3], [4]. Virtual reality interfaces have been proposed as tools to enhance training, by presenting realistically rendered practice conditions [5], [6] or by augmenting feedback [3], [7], [8]. While lacking in realism, these training systems perhaps owe their success to preserving features relevant to surgery. Training surgical skill then might be improved upon by focusing on features of the task environment that pose the greatest challenges. Simulated laparoscopy environments offer opportunities not only for enhancing training, but also as means to investigate the basis of manual dexterity in surgery.

Virtual environments allow focused study of individual aspects of control, such as the application of forces and presentation of visual feedback. Researchers have provided evidence that haptic perception is essential for laparoscopic manipulation [9], [10], [11], [12], [13]. Operators can successfully differentiate tissue properties [14]. The value of haptic cues, however, depends on physical factors such as the type of tissue or the resistance within the trocar [15]—the instrument that introduces the entry port. Along with haptic cues, perception of spatial information must contribute to surgical skill. Visualizing the operative environment [16] and perceiving depth given 2D visual feedback [17] both present challenges. Keehner et al. [18] showed that tests of spatial ability revealed predictors of surgical performance, in particular for novices. While it is clear that force interactions and spatial information clearly present challenges, the learner must in this context understand how the laparoscope itself functions.

Researchers have suggested that the nervous system employs specialized cerebellar processes for tools [19], adopts internal representations for objects with external degrees of freedom [20], and makes use of external coordinate systems appropriate for tool use. The sliding and pivoting action of the tool within the trocar represents a kinematic constraint, requiring specific compensation strategies to recover straight movements of the tip. In terms of online performance, Hodgson et al. found that both reversal and fulcrum effects increase task completion time relative to open surgery [21]. One possibility is that the motor system constructs a naïve representation of tool behavior, in which tip motion is a simple reversal of hand motion [22]. Such a representation potentially creates a stimulus-response conflict [23], [24] since a reversal may be unfamiliar and contradict existing motor schemes. On the other hand, the learner may successfully interpret tool use as a mapping between hand and tip motion, in which the mechanics of the tool are taken into account.

Rather than to validate the efficacy of a novel training environment, we seek to understand the underlying learning challenges inherent to laparoscopy. We focus here on how the kinematic constraints associated with laparoscopy contribute to skill acquisition. We developed an experiment testbed in which operators could practice controlling a virtual tool by moving a physical handle. While interactions with the trocar would typically introduce forces transmitted through the tool, this virtual interface could present virtual kinematic constraints *in the absence of haptic feedback*. We employed two forms of these relationships that would typically occur simultaneously in real tool operation during training. The interface was programmed to either respond to the absolute position or the orientation of hand motion, as measured from a sensor attached to the grip. We chose these formulations since they reflect the degrees of freedom of the task (three translations) versus that of the tool (two rotations and one translation), and therefore would support the learning of relevant neural representations. To determine which training best prepared the learner for the forces

expected from tool-trocar interactions, we tested skill transfer to actual physical constraints with haptic interactions.

Although the position and orientation modes of control described above allow the same movements in task space, we predicted that they would differ in terms of how they prepare learners for actual operation within the physical constraint. We expected that the representation of the tool in terms of orientation would more directly map to the proprioceptive apparatus of the motor system, and therefore be easier to use during training. However, we also expected that the representation of the tool in terms of absolute position would preserve critical features of mechanical contact, and hence be more relevant to actual operating conditions. In addition, we predicted that the fulcrum action of the tool would bias learning toward either emphasizing or hiding curvature of tip motion environment. These tests will reveal which kinematic relationships are critical to the nervous system for successful laparoscopic manipulation.

2 Methods

2.1 Human Subjects

In this study 42 healthy individuals, consisting of university students and researchers, were randomly assigned to three subject groups (two tests and one control). Expert surgeons and medical students were not selected for the current study. All participants reported having normal or corrected to normal vision. Each subject provided informed consent in accordance with Northwestern University Institutional Review Board. Individuals were not paid for their participation.

2.2 Experimental Apparatus

Subjects performed a virtual laparoscopy task by controlling the movement of a custom-made plastic handle with finger grips. During the task, subjects were presented with real-time feedback from a video display system known as Personal Augmented Reality Immersive System (PARIS) described elsewhere [25]. This video display system allowed both viewing of a large visual field and free movements of the hand in front of the user (see Fig. 2A). A cinema-quality digital projector (Christie Mirage 3000 DLP) displays the images over five-foot-wide $1,280 \times 1,024$ pixel image resulting in a 110 wide viewing angle. While no haptic device was connected to this interface, the position and orientation of the handle was tracked using a magnetic tracking system (Ascension Flock of Birds). This tracking system has a range of 0.75 m. The positions and angular resolutions (measured at 12 inches) are 0.5 mm and 0.1 degrees. A Flock-of-Birds sensor mounted to the grip allowed real-time measurement of both position and orientation of the handle. Using MATLAB and Simulink, we implemented a virtual surgical workspace, featuring a cubic environment (100 mm wide) with grid marking on the boundaries at 20 mm intervals. The port location was fixed at the top front edge of the workspace (see Fig. 2B). Data were recorded at 66 Hz, by sampling the Flock-of-Birds communication to Simulink. To interface with the virtual environment, subjects held the plastic handle with their fingers within the grips just as would occur with a traditional laparoscopic tool. Subjects sat facing the video display, such that the tool could comfortably be placed into the port, while the elbow was at 90 degrees (see Fig. 2A).

In a Simulink environment, we developed a program that computed the position and orientation of a virtual laparoscopic tool given real-time measurement of the handle. Data from the Flock-of-Birds system was interpreted in the Simulink model (UDP communication) and then used to drive animation displayed to the user. The program also controlled the presentation of starting and ending targets for each trial. It should be

emphasized that for this study no haptic feedback was presented to the user via a motorized device, though haptic sensations naturally occurred through passive interaction with the physical port. We describe the computation of the virtual laparoscopic tool motion in the following section.

2.3 Development of Virtual Environment

We investigated motor learning of environments that featured the kinematic constraints involved in laparoscopic manipulation. A novel virtual environment, developed in our laboratory represented the pivoting and sliding motion of a laparoscopic instrument, as shown in Fig. 2B. This environment mapped spatial movements (position and orientations) of a hand held tool into that of a virtual tool, while presenting different schemes for representing the kinematic constraints of laparoscopy. Real-time measurements of position and/or orientation of a handle were used as inputs to compute the movements of a virtual laparoscopic tool. We developed three different modes of operation (see Fig. 1), or constraint schemes: position-based, orientation-based, and physically based. In the physical constraint case, the tool was able to slide and pivot through a physical port. The motion of the virtual tool in this mode simply mirrored that of the physical handle. In the physically based constraint mode, the handle included a wooden dowel that was allowed pivoting and sliding through a hole (10 mm diameter) in a stationary plastic brace. The dowel was mounted to the dowel with cable tie connectors.

The next two modes exploit the capabilities only possible in virtual environments that allow an artificial decoupling of kinematic constraints. In the virtual constrained modes, the dowel and brace were omitted so that subjects operated the handle in free space. Instead of a mechanical constraint, the virtual environment maintained pivoting and sliding constraints for only the virtual tool. These two modes each replaced the presence of the physical port with a virtual one, with each of these accurately preserving one kinematic aspect while ignoring (sacrificing) the influence of the other. The virtual constraint described above represent two simple mathematical representations that faithfully translate motions of the hand into motions of the tool, while still preserving features of typical laparoscopy.

For the position-based constraint, the position of the handle of the virtual tool (x_h, y_h, z_h) coincided with that of the physical handle. With the position of the port (x_p, y_p, z_p) fixed, the orientation (θ_t, ϕ_t) of the virtual tool was completely determined:

$$\theta_t = \tan^{-1} \frac{y_p - y_h}{x_p - x_h}, \quad \phi_t = \tan^{-1} \frac{z_p - z_h}{\sqrt{(x_p - x_h)^2 + (y_p - y_h)^2}}. \quad (1)$$

With the orientation of the virtual tool computed, the final constraint to be satisfied is the length of the virtual tool L to completely define the tool tip position (x_t, y_t, z_t). While this constraint scheme is simple and faithfully represents the position of the physical handle, it ignores the orientation information from user input. For example, if the user applies pure rotations of the handle but does not change its position, no change results in the state of the virtual tool.

For the orientation-based constraint, the orientation of the virtual tool (θ_t, ϕ_t) corresponds to that of the physical handle (θ_h, ϕ_h). The linear translation of the tool, however, cannot follow that of the handle—otherwise the constraint to the port would not be maintained. Instead, the radial penetration of the virtual tool was calculated as the integrated motion of the handle projected along the tool axis. Given the linear velocity of the handle and the orientation (θ_h, ϕ_h) with respect to a global reference frame (i, j, k), the radial penetration of the virtual tool is

$$\Delta r_t = \int \dot{r}_h \cdot (\cos \varphi_h \cos \theta_h \hat{i} + \cos \varphi_h \sin \theta_h \hat{j} + \sin \varphi_h \hat{k}) dt. \quad (2)$$

The tool tip position (x_t, y_t, z_t) then maintains the length of the tool L while sliding by an amount equal to the computed change in radial penetration. Note that while the Orientation-Based constraint faithfully represents the orientation of the physical handle, it ignores any translation orthogonal to the axis of the virtual tool. For example, if the user moves the handle in pure translation, perpendicular to the axis of the tool, no change occurs in the state of the virtual tool.

2.4 Protocol

Subjects were asked to control the virtual tool so that the tip followed a target path as smoothly and accurately as possible. In each constraint mode, the video display presented the same visual feedback of the tool—a thin cylinder constrained within a virtual port (see Fig. 2B). The display presented visualization of target paths as a white beaded line (40 mm) between two target spheres (5 mm radius) at the endpoints. The trial ended when the tip was held within the final target for 1 second. To aid depth perception of the task, two features were used: first, the target starting and ending points were visualized as spheres atop two poles fixed to the floor of the workspace. Second, real-time shadows of the target path and tool were presented during movement (It should be noted, however, that in practical settings, shadows are typically not visible from the video display since the light source is placed near the camera). Each group was presented with the same sequence of randomized target locations. The virtual tool length was 330 mm.

To test how different kinematic constraints affected learning laparoscopic maneuvers, two subject groups trained using a virtual constrained tool. These subject groups (14 in each) differed by their constraint scheme (Position-Based or Orientation-Based). Both groups were evaluated in the physically based constraint condition before and after training. Groups were further subdivided into one of two target schedules: Near-Far-Near ($n = 14$) or Far-Near-Far ($n = 14$). Near (75 mm) and far (150 mm) targets were defined in terms of distance of the the starting target from the port. As an example, for a Near-Far-Near schedule, included primarily near trials in session-1 with an initial brief exposure (12 trials, near) followed by a long exposure (96 trials, far), and then a long exposure in session-2 (108 trials, near). These target schedules during training allowed a test of how practice at a certain target depth leads to skills that can transfer to other depths. Along with depth, we presented variations in the initial starting target position (heading and pitch angles, measured in spherical coordinates with respect to the port), and in path direction (left, right, up, and down). Table 1 summarizes the conditions and the schedule of the trial blocks within the experiment.

We performed a supplementary data collection featuring a Control group ($n = 14$) training only in the physically based constraint condition. Inclusion of the Control group allowed comparison of learning between the virtually and physically based constraint conditions, in particular with respect to sequence of targets near-far-near ($n = 7$) versus far-near-far ($n = 7$) training. The control group was presented with the same number of evaluation and training trials as the virtual training groups (see Table 1).

2.5 Data Analysis

We analyzed performance in terms of movement error and time, as means to measure accuracy and efficiency in movements. At each time step, the path error was computed as the distance along the line perpendicular to the target path to the tip position. As a final metric for path error, we considered the maximum perpendicular deviation from the direct path between targets. Movement time was simply calculated as the total duration of moving

between targets. To examine the change in learning, performance for both metrics was calculated as the percentage change between the initial and final evaluation for each unique condition of target heading and path direction. While path error represents a practical measure of kinematic performance, we also include task completion time since it reflects economy of movement. Second, including these metrics allows a check for potential compromise between speed and accuracy.

In addition to evaluation blocks, we present an analysis of the changes in performance during training. To determine which conditions pose the greatest challenge to learning, we compared performance between constraint schemes and between training schedules. To determine how practice with near and far target distances (75 or 150 mm) transferred skill to each other during training, we analyzed how performance changed between the first 12 trials of each block (Far-Near-Far or Near-Far-Near transfer). Using 12 trials for both the initial and final evaluation during training allowed for 1) a balanced comparison of the impact of intervening trials, and 2) a measure of the immediate transfer effect that does not reflect further acclimatization to test conditions.

To analyze the change between evaluation blocks, we performed ANOVA (analysis of variance) considering both the between and within-subject experiment factors. The between subject factors included the constraint scheme (Position-Based, Orientation-Based, or Control) and target schedule (Near-Far-Near/Far-Near-Far), while the within-subject factors included target heading (angle about the vertical: 67.5, 90, 112.5 degree), and path direction (left, right, up, down). Note that for the evaluation trials analysis, the between-subject factors pertain to conditions experienced during training, while within-subject factors pertain to evaluation conditions.

Similarly, to assess performance during the training trials, we performed ANOVA considering the between-subject factors: constraint scheme (Position-Based, Orientation-Based, Control), target distance (near/far); and within-subject factors: target pitch (target angle about the horizontal: -33, 0 degree), target heading (angle about the vertical: 67.5, 90, 112.5 degree), and path direction (left, right, up, down). For ANOVA results, we report the F-statistic, effect and error degrees of freedom, p-value, and Mean Squared Error (MSE). We performed Tukey's posthoc Honest Significant Difference (HSD) to determine how group differences depended on specific task conditions for all cases where more than two groups are compared. The threshold level of significance for both ANOVA and posthoc tests was $\alpha = 0.05$. Confidence Intervals (CIs) are reported at 95 percent.

3 Results

The results section is organized as follows: we first discuss how experimental conditions introduced systematic error with the physical port evaluations and then determine whether training reduced this error for each training condition (Section 3.1). We then discuss the differences in learning due to constraint scheme (Section 3.2) and due to insertion depths (Section 3.3). Finally, we discuss how some of the trends observed for the physical evaluations were similar to those seen during training to determine what kinematic features most contribute to the challenges of the physical port (Section 3.4).

3.1 Main Effects Influencing Error

Throughout the experiment, subjects deviated the most from a straight line in the vertical directions of movement (see Fig. 3). Subjects exhibited systematic deviations from straight-line movement in the evaluation blocks, which were consistent with a failure to compensate for tool rotation. Performance varied by path direction (path error: $F[3,105] = 55.99$, $MSE =$

720.9, $p < 0.001$); movement time: $F[3,105] = 11.41$, $MSE = 77.35$, $p < 1e-33$). These patterns of error likely reflect greater visual occlusion (by the tool) for these path directions.

As expected, training significantly improved performance. Groups benefitted from training (see Fig. 4), as evidenced by improved performance between evaluation blocks (path error: $F[1,24] = 16.67$, $MSE = 534.91$, $p < 1e-3$; movement time: $F[1,24] = 51.50$, $MSE = 1406.36$, $p < 1e-3$). By individual groups (according to T-tests), Position-Based (mean change: -22.2 percent; CI: $-29.9, -14.6$; $p < 1e-3$, T-test) and the Control (mean change: -29.4 percent; CI: $-38.7, -20.1$; $p < 1e-3$) training resulted in significant improvement in path error, while the improvement from Orientation-Based training was not significant (mean change: -8.8 percent, CI: $-20.0, 2.4$; $p = 1.10e-1$, T-test). The Orientation-Based (mean change: -29.1 ; CI: $-35.8, -22.5$; $p < 1e-3$), Position-Based (mean change: -25.3 percent; CI: $-38.5, -12.1$; $p = 1.12e-3$), and Control training groups each exhibited significant reductions in movement time.

3.2 Learning Differences Due to Constraint Scheme

After confirming that learning occurred for each group, we checked for differences in learning *between* groups. We found that training with the Position-Based and the Control condition had similar advantage over Orientation-Based in terms of path error. Position-based training exhibited a trend of greater path error improvements compared to Orientation-Based training (mean difference: 14.0 percent; CI: $0.7, 28.6$; $p = 6.48e-2$; Tukey HSD). Subjects who trained in the Control condition exhibited reductions in path error significantly greater than the Orientation-Based group (mean difference: -21.0 percent; CI: $6.0, 35.9$, $p = 4.18e-3$; Tukey HSD), and similar reductions relative to the Position-Based group (mean difference: -7.0 percent; CI: $-21.9, 7.9$, $p = 4.91e-1$; Tukey HSD). These findings indicate close similarities in learning between the Control and Position-based constraint conditions.

The training advantage of Position-based constraint was particularly evident for downward movements (mean difference 37.1 percent; CI: $11.0, 63.3$; $p < 1e-3$; Tukey HSD). While analysis of path error indicated marginal overall differences between virtual constraint groups, we detected significant differences between these groups in specific path directions ($F[3, 72] = 5.87$, $MSE = 1.96$, $p = 1.21e-3$). The Control group exhibited a similar advantage over the Orientation-Based condition in downward movements (mean difference 30.7 percent; CI: $4.1, 57.4$; $p = 9.89e-3$; Tukey HSD). Similar trends occurred for other path directions. This dependence on path direction suggests that Position-Based training was particularly important for difficult movements, since downward movements typically exhibited the largest error during initial evaluations. Constraint groups exhibited overall differences in reducing movement time ($F[2, 35] = 3.52$, $MSE = 2.81$, $p < 1e-3$), yet pairwise comparisons did not indicate significant differences. Training in the Control condition resulted in a trend of greater reductions than Position-Based (mean difference: -17.5 percent; CI: $-36.7, 1.78$; $p = 8.22e-2$, Tukey HSD). This effect varied by heading angle ($F[4, 70] = 1.33$, $MSE = 0.16$, $p = 4.32e-2$), though comparisons for specific task conditions did not reveal significant group differences.

3.3 Learning Differences Due to Insertion Depth

Interestingly, practicing with shallower tool insertion resulted in more reduced movement time ($F[1, 35] = 10.90$, $MSE = 8.70$, $p = 2.21e-3$; mean difference 13.5 percent; CI: $7.5, 19.5$), but did not greatly impact path error ($F[1, 35] = 3.47$, $MSE = 2.05$, $p = 7.11e-2$; mean difference 8.3 percent; CI: $-2.8, 19.4$). Subjects that trained with predominantly shallow targets (the Near-Far-Near schedule) reduced their movement time by 20.5 ± 18.9 percent, which was greater than the 34.0 ± 14.8 percent reduction in subjects who predominantly

trained with deep targets (the Far-Near-Far schedule). These trends were similar for each constraint group.

3.4 Performance during Training

To explain why there were differences between Position and Orientation-Based training, we further focused on the performance during the training phase. As shown in Fig. 5, training with the Position-Based constraint exhibited greater path error (mean difference: 3.04 mm; CI: 1.89, 4.20; $p < 1e-3$, T-test) and movement time (mean difference: 3.41 sec; CI: 2.16, 4.66; $p < 1e-3$, Tukey HSD) compared to the Orientation-Based constraint.

Interestingly, subjects who trained with the Position-Based constraint exhibited particularly high error in certain path directions. For example, path error was greater in downward versus leftward (mean difference: 1.04 mm, CI: 0.37, 1.72; $p < 1e-3$, Tukey HSD) and rightward directions (mean difference: 0.94 mm, CI: 0.26, 1.62; $p = 2.02e-3$, Tukey HSD). As shown in Fig. 5, movement trajectories exhibited greatest systematic error in vertical directions. Movement time was also greater in upward versus leftward directions (mean difference: 1.19 mm, CI: 0.12, 2.25; $p = 2.19e-2$, Tukey HSD). These findings mirror the systematic errors found in evaluation trials, which further confirm the similarities between Position-Based and the control condition.

We also confirmed successful skill transfer from near to far targets only for the group practicing the Position-Based constraint (path error mean difference -15.0 percent; CI: -30.0 , 1.0 ; T-test, $p = 4.36e-2$, based on the first 12 trials of each block). These trends suggest again that training with shallow targets transfers better to deep targets than vice-versa, perhaps due to the lever amplification effect that is only present with the Position-Based constraint. These findings show that the benefits of training with shallow targets not just due to mechanical leverage, but must also arise purely from kinematic relationships.

4 Discussion

We devised an interactive virtual environment in which subjects performed laparoscopic maneuvers with and without mechanical contact. Our virtual environments featured either the sliding (Position-Based) or pivoting (Orientation-Based) features of laparoscopy, in the absence of mechanical interaction. Both of these virtual constraint schemes led to improvements in performance—a result which demonstrates that the kinematic features of laparoscopy are indeed vital to actual tool use. Our primary finding was that Position-Based training was most beneficial in transferring skills to the final (physically based) evaluation. This result was intriguing since pilot experimentation with surgeons suggested that the Orientation-Based constraint was more intuitive. Second, our analysis suggests that training with shallow targets promotes greater reduction in movement time.

The greater improvement in performance seen with Position-Based practice implies that it is more important to provide a training environment that preserves the features of the absolute position rather than hand orientation. The perceptual-motor system has been shown to prefer a joint-based coordinate system for certain degrees of freedom of the arm [26], or for adaptation to novel environments [27]. However, in laparoscopy, the external constraints of the tool mean that one can rely on proprioception alone; one must construct them using visual feedback. To this end, the Position-Based constraint may have presented a more realistic challenge since this condition preserved the features of absolute space, whereas the Orientation-Based system violates the physical constraint of the position of the hand in order to represent the virtual tool.

The Position-Based constraint posed a greater challenge to learning, as evidenced by the larger error and longer task time during training. Movement trajectories during Position-Based training suggest incomplete compensation of tool rotation, in a manner similar to that observed in the control condition. Using a virtual environment similar to our Position-Based constraint, Sülzenbrück and Heuer [28] found that subjects did not exhibit appropriately curved handle trajectories when adapting to a virtual sliding lever. Evidently, experiencing the errors during Position-Based training provided information that was relevant to the physical constraints of the evaluation task.

Beyond differences in constraint groups, we found that the training focused on shallow insertion provided greater reductions in movement time. Because the trocar acts as a fulcrum for the tool, there is a natural amplification/attenuation effect between the hand and tool tip movement. A lower mechanical advantage amplifies movements of the tool tip relative to the hand, potentially providing heightened feedback about hand motion. Consequently, it was plausible that practice with farther targets could have had benefits. Our data cannot reveal whether such improvements in movement time might come at some cost to reducing path error; the trend of greater path error reductions from training in deep insertion was not significant. These results, however, do suggest that the primary impact of training with shallow insertion was to allow greater efficiency in movement.

Previous studies have shown that augmentation of error feedback can enhance learning [21], presumably because such amplified feedback provokes greater changes to motor planning. Increasing awareness of tool behavior could promote the learning of more efficient movement strategy. Besides amplification, the pivoting action of the tool creates curvature of the tip motion requiring compensatory actions from the user. Jordan et al. [29] found that virtual laparoscopy training featuring more movement reversals prepared novice learners better for an incision skill transfer test. They argued that more exposure to the reversal actions due to fulcrum rotation allowed training more relevant to the target task. Our own findings follow a similar argument with respect to curvature of movement. To enforce a straight right-to-left movement of the tool tip, the hand must move along a curved left-to-right path. If the length of the tool is L , the distance between the targets is $2 \cdot d$ and the distance of the fulcrum to the targets is ϵL (with $d/L < \epsilon < 0.5$), then to produce a straight path of the tool's endpoint, the hand must deviate from a straight path by a quantity

$$\delta = L \cdot \left(1 - \sqrt{1 - \frac{d^2}{L^2 \epsilon^2}} \right). \quad (3)$$

This is a decreasing function of ϵ : as the distance between fulcrum and targets decreases for shallower targets, the hand must move farther away from the straight path that would naturally be produced in a reaching movement. Stated differently, if the hand moves in the natural straight path from start to end position, the tip of the tool generates larger tracking errors when the targets are closer to the fulcrum, then when they are distal. Furthermore, tip motion becomes increasingly slower with shallow insertion. Hence, when training in shallow insertion subjects are exposed to greater challenges and must learn appropriate compensatory strategies.

Our results have important implications for the role of haptic feedback in laparoscopic surgery. Investigators have debated on whether tactile feedback is necessary for training of laparoscopic skill [12], [13], [14]. While our study's key feature is virtual tool use in the absence of haptic feedback, our findings show that such training can influence skills needed for successful compensation of forces arising from passive interaction of the tool and trocar. Researchers have proposed hierarchical control [30], wherein the motor cortex and spinal

cord are responsible for basic inverse model prediction, while the cerebellum mediates compensation for interaction forces [31]. We suggest then that investigations of tool use should consider how an understanding of underlying kinematic relationships could impact both motor performance and perception in haptic interactions. Insertion depth must certainly effect the transmission of force. Hence, further investigation is needed for how faulty understanding of kinematic relationships in laparoscopic tool use might distort perception of tissue stiffness, for example. Furthermore, it is likely that haptic information would be directly informative of the kinematic relationships described in this study. Additional study is needed to determine how tooltip contact forces might compound the learning challenges observed in this study.

Our investigation reflects a scenario where the tool-trocar interaction is the principal challenge to learning. We emphasize that the virtual constraints examined in this study are not intended to replace training with physically based constraints typical of box-trainers. We also stress that this study does not reveal to what extent kinematics of laparoscopy pose fundamental limitations to performance for expert level surgeons. Our results imply that training of laparoscopy should emphasize training with near targets since such practice can successfully transfer to conditions with deeper insertion. Furthermore, our findings suggest that learners should focus attention on the absolute position of their grip relative to the port in order to minimize movement error. These patterns of learning could impact the design of surgical simulators or simply influence instructions to students during training.

This study provides insights for a simplified model of laparoscopic tool-use that nonetheless could offer recommendations to improve surgical training. This investigation demonstrates how virtual environments can be used to decouple different fundamental features of a task to understand how the nervous system acquires and executes effectual control. It remains to be seen whether absolute spatial relationships and the working insertion depth constitute the most critical learning challenges to mastering dexterity in laparoscopy. However, it is likely that the simple tool mechanics considered in this study interacts with the challenges of complex real-world environments. Critical skills in laparoscopic surgery such grasping, cutting, transporting tissue, coordination between hands in suturing must all be expressed through kinematic relationships considered in this investigation.

Acknowledgments

This work was supported by NINDS grants NS053581 and NS053606, the US-Israel Binational Science Foundation—2007195, and by the Coolidge Foundation.

References

1. Laguna, M., et al. Training in Laparoscopy. In: Rosette, J.; Gill, I., editors. *Laparoscopic Urologic Surgery in Malignancies*. Springer Berlin Heidelberg; 2005. p. 253-269.
2. Scott HJ, Darzi A. Tactile Feedback in Laparoscopic Colonic Surgery. *British J. Surgery*. 1997 Jul.vol. 84:1005.
3. Downes M, et al. Virtual Environments for Training Critical Skills in Laparoscopic Surgery. *Studies in Health Technology and Informatics*. 1998; vol. 50:316–322. [PubMed: 10180560]
4. Tendick F, et al. Comparison of Laparoscopic Imaging Systems and Conditions Using a Knot-Tying Task. *Computer Aided Surgery*. 1997; vol. 2:24–33. [PubMed: 9148876]
5. Lemole GMJ, et al. Virtual Reality in Neurosurgical Education: Part-Task Ventriculostomy Simulation with Dynamic Visual and Haptic Feedback. *Neurosurgery*. 2007; vol. 61:142–149. [PubMed: 17621029]
6. Liang S, et al. A High Performance Graphic and Haptic Curvilinear Capsulorrhesis Simulation System. *Proc. IEEE Ann. Int'l Conf. Eng. in Medicine and Biology Soc.* 2009; vol. 2009:5092–5095.

7. Wierinck E, et al. Effect of Reducing Frequency of Augmented Feedback on Manual Dexterity Training and Its Retention. *J. Dentistry*. 2006; vol. 34:641–647.
8. Teber D, et al. Augmented Reality: A New Tool to Improve Surgical Accuracy during Laparoscopic Partial Nephrectomy? Preliminary in Vitro and in Vivo Results. *European Urology*. 2009 Aug.vol. 56:332–338. [PubMed: 19477580]
9. Kim HK, et al. Virtual-Reality-Based Laparoscopic Surgical Training: The Role of Simulation Fidelity in Haptic Feedback. *Computer Aided Surgery*. 2004; vol. 9:227–234. [PubMed: 16192064]
10. Wagner CR, Howe RD. Force Feedback Benefit Depends on Experience in Multiple Degree of Freedom Robotic Surgery Task. *IEEE Trans. Robotics*. 2007 Dec; vol. 23(no. 6):1235–1240.
11. Reiley CE, et al. Effects of Visual Force Feedback on Robot-Assisted Surgical Task Performance. *J. Thoracic Cardiovascular Surgery*. 2008 Jan.vol. 135:196–202.
12. Botden SM, et al. The Importance of Haptic Feedback in Laparoscopic Suturing Training and the Additive Value of Virtual Reality Simulation. *Surgical Endoscopy*. 2008 May.vol. 22:1214–1222. [PubMed: 17943369]
13. Tholey G, et al. Force Feedback Plays a Significant Role in Minimally Invasive Surgery: Results and Analysis. *Annals of Surgery*. 2005 Jan.vol. 241:102–109. [PubMed: 15621997]
14. Lamata P, et al. Understanding Perceptual Boundaries in Laparoscopic Surgery. *IEEE Trans. Biomedical Eng.* 2008 Mar; vol. 55(no. 3):866–873.
15. Picod G, et al. What Can the Operator Actually Feel When Performing a Laparoscopy? *Surgical Endoscopy*. 2005; vol. 19:95–100. [PubMed: 15772876]
16. Zaid H, et al. Integrating Surgical Skills Education into the Anatomy Laboratory. *J. Surgical Research*. 2010 Jan.vol. 158:36–42.
17. Shah J, et al. Depth Cue Reliance in Surgeons and Medical Students. *Surgical Endoscopy*. 2003 Sep.vol. 17:1472–1474. [PubMed: 12802650]
18. Keehner MM, et al. Spatial Ability, Experience, and Skill in Laparoscopic Surgery. *Am. J. Surgery*. 2004 Jul.vol. 188:71–75.
19. Imamizu H, et al. Human Cerebellar Activity Reflecting an Acquired Internal Model of a New Tool. *Nature*. 2000 Jan.vol. 403:192–195. [PubMed: 10646603]
20. Dingwell JB, et al. Experimentally Confirmed Mathematical Model for Human Control of a Non-Rigid Object. *J. Neurophysiology*. 2004 Mar.vol. 91:1158–1170.
21. Hodgson AJ, et al. The Effects of Physical Constraints in Laparoscopic Surgery. *Medical Image Analysis*. 1999 Sep.vol. 3:275–283. [PubMed: 10710296]
22. Sharp I, et al. Visual Error Augmentation Enhances Learning in Three Dimensions. *Proc. IEEE Ann. Int'l Conf. Eng. in Medicine and Biology Soc.* 2010; vol. 1:5915–5918.
23. Wuhr P. Working-Memory Load Decreases Mappings Effects in Spatial-Compatibility Tasks. *Psychological Research*. 2010 Dec; vol. 15(no. 5):393–405. [PubMed: 21184095]
24. Rubichi S, et al. Right-Left Prevalence with Task-Irrelevant Spatial Codes. *Psychological Research*. 2005 Jan.vol. 69:167–178. [PubMed: 15597182]
25. Patton JL, et al. Evaluation of Robotic Training Forces that Either Enhance or Reduce Error in Chronic Hemiparetic Stroke Survivors. *Experimental Brain Research*. 2006 Jan.vol. 168:368–383.
26. Darling WG, Gilchrist L. Is There a Preferred Coordinate System for Perception of Hand Orientation in Three-Dimensional Space? *Experimental Brain Research*. 1991; vol. 85:405–416.
27. Shadmehr R, Mussa-Ivaldi FA. Adaptive Representation of Dynamics during Learning of a Motor Task. *J. Neuroscience*. 1994 May.vol. 14:3208–3224.
28. Sulzenbruck S, Heuer H. The Trajectory of Adaptation to the Visuo-Motor Transformation of Virtual and Real Sliding Levers. *Experimental Brain Research*. 2010 Mar.vol. 201:549–560.
29. Jordan JA, et al. Virtual Reality Training Leads to Faster Adaptation to the Novel Psychomotor Restrictions Encountered by Laparoscopic Surgeons. *Surgical Endoscopy*. 2001 Oct.vol. 15:1080–1084. [PubMed: 11727074]
30. Gao F, et al. Neural Network Modeling Supports a Theory on the Hierarchical Control of Prehension. *Neural Computing and Applications*. 2004; vol. 13:352–359.
31. Schweighofer N, et al. Role of the Cerebellum in Reaching Movements in Humans. I. Distributed Inverse Dynamics Control. *European J. Neuroscience*. 1998 Jan.vol. 10:86–94.

Biographies

Felix C. Huang received the BS degree in mechanical engineering from the University of California at Berkeley and the PhD degree in a combined mechanical/industrial engineering at the University of Michigan, in 1997 and 2006, respectively. He worked as a full-time science teacher with the Teach for America program from 1997 to 1999 in East Palo Alto, California. Currently, he is working as a postdoctoral fellow at Northwestern University, Department of Biomedical Engineering, and a research associate at the Rehabilitation Institute of Chicago (RIC). His professional interests include rehabilitation robotics, surgical training, motor learning, modeling of motor control, human factors, mechatronics, haptics rendering, and science education. His recent work demonstrated how motor learning in manual control can be facilitated with the use of destabilizing forces. He is a member of the IEEE, Society for Neuroscience, and Society for the Neural Control of Movement.

Ferdinando A. Mussa-Ivaldi received the graduate degree (Laurea) in physics from the University of Torin, and the PhD degree in biomedical engineering from the Politecnico di Milano. He is a professor of physiology, physical medicine and rehabilitation, and biomedical engineering at Northwestern University. He is a director of the Robotics Laboratory of the Rehabilitation Institute of Chicago. Before joining the faculty at Northwestern, he was a principal research scientist in the Department of Brain and Cognitive Sciences at MIT. His areas of interests and expertise include robotics, neurobiology of the sensory-motor system and computational neuroscience. His research interest is primarily focused on the mechanisms of motor learning. He uses robotics and virtual reality to enhance the acquisition of motor skills in healthy and disabled people. Among his achievements are the first measurement of human-arm multijoint impedance, the development of a technique for investigating the mechanisms of motor learning through the application of deterministic force fields, the discovery of a family of integrable generalized inverses for redundant kinematic chains, the discovery of functional modules within the spinal cord that generate a discrete family of force fields, the development of a theoretical framework for the representation, generation and learning of limb movements and the development of the first neurorobotic system in which a neural preparation in-vitro—the brainstem of a lamprey—controls the behavior of a mobile robot through a closed-loop interaction. He is a member of the IEEE, Society for Neuroscience, and Society for the Neural Control of Movement.

Carla M. Pugh received the BA degree from the University of California, Berkeley, the MD degree from Howard University in 1988 and 1992, respectively, and the PhD degree in education from Stanford University in 2001, after completion of the surgical training at Howard University Hospital in 1997. In 2003, she became assistant professor of surgery at Northwestern University and was promoted to associate professor in 2010. She is a director of Northwestern's Center for Advanced Surgical Education and also holds an adjunct professorship in Northwestern's School of Education and Social Policy. She has been an invited editor for a number of medical and engineering journals and serves on committees for the American College of Surgeons, Association for Academic Surgery, and Medicine Meets Virtual Reality. Her work has been recognized in Wired Magazine, New York Times, Reuters, BBC News, Chicago Sun Times, and National Public Radio. Her research is grounded in a special interest in the use of sensors and data acquisition technology for assessing hands-on clinical skills. As a graduate student, she developed her first training tool using this technology and was awarded a method patent by the US Patent Office. She has received numerous grant awards for her work and is also the recent recipient of a National Institutes of Health R-01. This funding will be used to validate one of her sensorized training models for high stakes clinical examination skills.

James L. Patton received the BS degree in mechanical engineering and engineering science from the University of Michigan, the MS degree in theoretical mechanics from Michigan State University, and the PhD degree in biomedical engineering from Northwestern University. Currently, he is working as an associate professor of bioengineering at The University of Illinois at Chicago and as an associate director of the Center for Rehabilitation Robotics at the Rehabilitation Institute of Chicago (RIC). He also holds affiliate positions in physical medicine and rehabilitation, and mechanical and biomedical engineering at Northwestern University. He has worked in manufacturing for Ford and as a cyclotron operator in nuclear medicine before turning his attention to biomechanics and control of human movement. His general interests include robotic teaching, dynamic balance control, haptics, modeling of the human-machine interface, and robot-facilitated recovery from a brain injury. His research has demonstrated how control is made robust by avoiding undesirable situations. His more recent research has demonstrated how one can exploit the nervous system's natural capacity to adapt in order to teach movements and help people to recover from brain injury. He is on the International Advisory Committee for the IEEE-EMBS and also chairs the technical committee on biomedical robotics. He is a member of the IEEE.

Fig. 1.

We examined three representations of the kinematic constraints of laparoscopic manipulation. The physically based constraint (left) is consistent with the mechanics of the actual laparoscopic port. The position based (center) and orientation based (right) constraints are mathematical representations that reproduce specific kinematic features of the physical constraint without limiting the physical motion of the hand. The position based constraint removes the contribution of hand rotation, whereas the orientation based constraint removes the contribution of hand translation. Evaluation trials featured the physically based constraint, while training trials featured either position based or orientation based constraints. In the physically based mode, the virtual tool tip (green) follows the full motion of the operator's input (orange) as constrained by a physical port. In the position based constraint, the virtual tool tip (x_t, y_t, z_t) is defined by a line of length L , constrained through the port (x_p, y_p, z_p) and the hand positions (x_h, y_h, z_h). In the orientation-based constraint, the virtual tool mirrors the orientation ($\theta_t; \phi_t$) and radial motion (Δr) of the physical tool.

A. User Interface and Apparatus

B. Visual Display of Task Environment

Fig. 2.

(A) While seated in front of a large video display, subjects controlled the motion of a hand-held grip, containing position and orientation sensors. The tool could be operated with 1) a shaft constrained physically within a port (5 mm diameter) in a plastic tube, supported by braces against the floor and the display screen, or 2) without the physical shaft for virtual constraint operation. (B) The visual display provided real-time feedback of the virtual surgery environment. Subjects attempted to control the tool (cyan) tip to move smoothly and accurately along a path (white beaded line). Starting targets varied in insertion depth R , heading angle θ , and pitch angle ϕ (not shown). The movement directions were left, right, up, or down. In all conditions, the video display presented the same visual feedback of the tool constrained within a virtual port.

Fig. 3.

Evaluation following training (physically based constraint) revealed average trajectories with systematic deviations from the ideal paths (black dashed) along the four movement directions (averaged over all target heading and pitch angles). Lower deviations were evident from Position-Based and Far-Near-Far virtual constraint training, in particular in the upward and downward directions. Coloring indicates progression in time, starting from red and ending in blue.

Fig. 4. Different training conditions resulted in two significant changes in the evaluations condition (with a physically based constraint). First, training with Position-Based virtual kinematic relationship resulted in greater reductions in path error (group mean with 95 percent CI) compared to the Orientation-Based constraint. Second, training with predominantly shallow insertion (Near-Far-Near) resulted in greater reductions movement time compared to deep insertion (Far-Near-Far), but did not differ significantly in reducing path error.

Fig. 5.

During training, the average trajectories for vertical movements (shown w/95 percent CI) for training blocks at near (75 mm) and far (150 mm) targets reveal systematic error patterns for Position-Based control. These systematic deviations were similar to those found for the Control group (physically based constraint). These patterns suggest that subjects do not fully compensate for the intrinsic curvature due to kinematic constraints of sliding and pivoting tool action, especially at pitch angles away from center.

TABLE 1

Experiment Conditions

Tool Length:	330 mm
Starting Target Location:	
ϕ , pitch (Low, High)	$-33, 0^\circ$
θ , heading	67.5, 90, 112.5°
R, distance (Near, Mid, Far)	75, 100, 150 mm
Path direction:	Left, Right, Up, Down
Session 1:	
1. Baseline Evaluation (Physical Constraint)	
24 Trials, 2 replicates	
Targets: R=100 mm, $\phi=-33^\circ$, all headings, all directions	
2. Training (Virtual or Physical Constraint)	
108 trials Per Session, 4 replicates	
Practice Schedule:	Near $\times$ 12, Far $\times$ 96 or Far $\times$ 12, Near $\times$ 96
Session 2:	
3. Training (Virtual or Physical Constraint)	
108 trials Per Session, 4 replicates	
Practice Schedule:	Near $\times$ 108 or Far $\times$ 108
4. Transfer Evaluation (Physical Constraint)	
(Same conditions as baseline Evaluation)	