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Experimental Performance Evaluation of a Haptic Training Simulation System

Behzad Khademian and Keyvan Hashtrudi-Zaad

Abstract— **In this paper the performance of a dual-user haptic simulation system with a proposed shared control architecture is experimentally evaluated for a specific trajectory following task under different operating conditions. The multilateral control architecture developed for training purposes, allows interaction between both users, the trainee and the trainer, as well as between the users and the virtual slave robot in a shared environment. The performance of the architecture is evaluated experimentally in terms of the effect of environment point of view, environment mushiness, and the existence of virtual fixtures. The performance is measured against task completion time, the path following accuracy and energy exchange by the trainer and the trainee.**

I. Introduction

It is known that haptic feedback increases the sense of realism and presence in robotic interaction with virtual objects. There has been a significant amount of work reported on the effect of haptic feedback on the performance of single-user haptic systems [1], [2], [3], [4]. In the haptic guidance steering experiment in [1], predictive forces have been used, and compared to the situation with baseline forces and without guidance. User studies showed the effectiveness of predictive forces for the steering task.

In [2], the effect of haptics and visuohaptics have been investigated in a 3D path learning. Subjects were asked to reproduce the trajectories with the specific shapes in 3D space. The experiments showed that haptic plus visual feedback results in better performance in terms of spatial error and time. Morris *et al.* [3] have investigated the use of haptic feedback and visuohaptic in learning a sequence of forces along a trajectory. They found out that visuohaptic training improved the performance, which was measured in terms of the accuracy of force recall.

The above works have studied the effect of haptic and visual feedback in subject performance in single-user haptic systems. However, they did not consider the different aspects of haptic and visualization in the performance, such as type of environment and environment point of view.

A recent research area is collaborative haptics and telemanipulation in which multiple users interact with each other to perform a task cooperatively on a shared environment. Emerging application of such systems is in *human haptic guidance* for medical training [5] and surgery [6], [7] in which two users interact with each other via two haptic interfaces manipulating a shared real or virtual environment.

A user study by Basdogan *et al.* [8] has shown that the use of haptics in addition to visual aid in a shared virtual environment can facilitate the sense of being and collaboration with a remote partner through reduced task completion time. In [9], Khademian *et al.* have developed a collaborative haptic training system and quantified the skill of trainees based on the accuracy of path recall in a trajectory following task. However, they have used haptic feedbacks with no visual cue in their training sessions.

In this paper, a multilateral shared control architecture is proposed and implemented on a haptic simulation testbed consisting of two Planar Twin Pantograph haptic devices and a simulated Pantograph as the slave robot. The performance of the proposed collaborative haptic controller is experimentally evaluated in the presence of visual and haptic feedback for a specific task of following a square path. To measure the performance, in addition to task completion time, we will introduce two performance indices based on the accuracy of the traversed path and the amount of energy exchanged. We will also investigate the effect of *environment point of view*, *environment mushiness*, and the existence of *virtual fixtures* in human haptic guidance in the above trajectory following task. Furthermore, we will show how the performance is affected as the trainer authority over the task is shifted to the trainee in each of the above mentioned experimental conditions.

The remainder of the paper is organized as follows: The description of the dual-user teleoperation system with the proposed multilateral shared control architecture is briefly given in Section II. The user study experiment is designed in Section III. The performance measures are introduced and the performance of the proposed architecture is evaluated in Section IV. The effects of operating conditions on performance are discussed in Section V. The paper concludes in Section VI.

II. Dual-user Haptic Simulation System

The dual-user haptic simulation system consists of two master robots for two users and one slave robot to perform a task on an environment. Figure 1 shows the detailed block diagram of the proposed shared control architecture. In this architecture, the slave robot is controlled based on the users' authority over the dominance factor, α, which varies between zero and unity. The control authority of user 1 and user 2 over the slave robot are determined by α and $1-\alpha$, respectively. Therefore, the position and force commands to the slave

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The authors are with the Department of Electrical and Computer Engineering, Queen's University, Kingston, ON K7L 3N6, Canada. Emails: 5bk@qlink.queensu.ca and khz@post.queensu.ca

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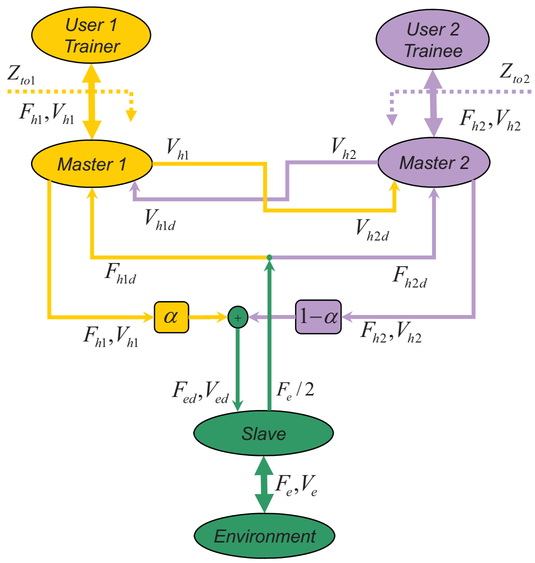


Fig. 1. Block diagram of the proposed multilateral shared control architecture.

robot are a weighted sum of the positions and forces of the other two robots, as follows

$$V_{ed} = \alpha V_{h1} + (1-\alpha) V_{h2} \tag{1}$$

$$F_{ed} = \alpha F_{h1} + (1-\alpha) F_{h2} \tag{2}$$

in which V_{h1}, V_{h2}, F_{h1} and F_{h2} denote users positions and forces applied to their master robots. In this architecture, the two masters are bilaterally connected via position channel for position correspondence. Therefore, the desired position signals for masters are set according to

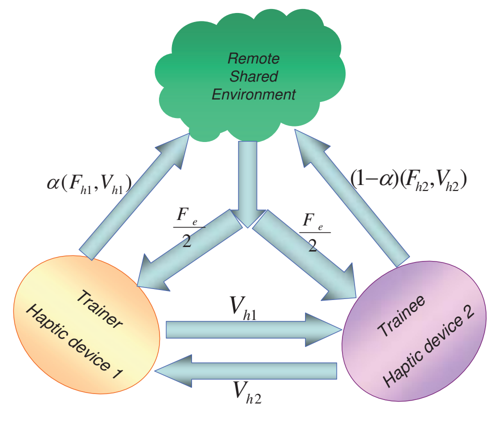
$$V_{h1d} = V_{h2} \tag{3}$$

$$V_{h2d} = V_{h1} \tag{4}$$

which increase the maneuverability of both users. For users to feel the environment, there should always be some level of feedback from environment to each haptic device. Figure 2 shows the signal flow in the proposed control architecture. In this architecture half of the environment forces F_e, is fed back to each master, that is

$$F_{h1d} = F_{h2d} = \frac{F_e}{2} \tag{5}$$

The effect of the other half is indirectly received via V_{hid}, $i = 1, 2$. The master and slave local and remote controller blocks are chosen according to the transparency-optimized control law introduced in [10] guaranteeing position and force following.
In this architecture when $\alpha = 1$ (training mode), the virtual slave robot receives command only from the trainer. Therefore, the slave robot is in interaction with the trainer, and the trainee only receives force signal from the environment for telepresence. By decreasing α to 0.5 (guidance mode), the trainer and the trainee have balanced dominance over the slave. In this case, both users experience the same feel of the environment. To give full authority to the trainee, α should be shifted to 0 (evaluation mode). Then, the trainee is in full control of the slave robot. In all of the above three cases, the trainer is able to correct trainee's motion through the bilateral connection between the two masters.
In the next section, we will design an experiment and a user study will be carried out to evaluate the performance of the proposed control architecture.



(a)

Fig. 2. Desired positions and forces in the proposed architecture.

III. Experiment Design

A. Experimental Setup

The controller is implemented on a dual-user haptic simulation system consisting of two 3-DOF Planar Twin Pantograph haptic devices that interface the users with a simulated model of a 3-DOF Planar Twin Pantograph as the virtual slave, and an LTI mass-damper-spring dynamic model representing a virtual environment (Figure 3). The users hand forces are measured by two Nano25 force/torque sensors providing a force resolution of $1/48\ N$ in x and y horizontal directions.

B. Experimental Procedure

A series of tests are conducted in which the trainer (user 1) guides the trainee (user 2) on how to lead the slave robot to follow a $100 \times 100\ mm$ square path. Both the trainer and the trainee are able to see the desired square path and the actual track of the slave on the monitor as shown in Figure 4.

1) Environment Viewpoint: To investigate the effect of environment viewpoint, the experiments are conducted in two different cases in which the users can see the environment: i) from top (Figures 4(a)) and ii) from front with the angle of view of 30° (Figures 4(b)).

2) Environment: To investigate the effect of environment, experiments have been carried out in three different operating conditions:

i. The slave robot is in free motion.

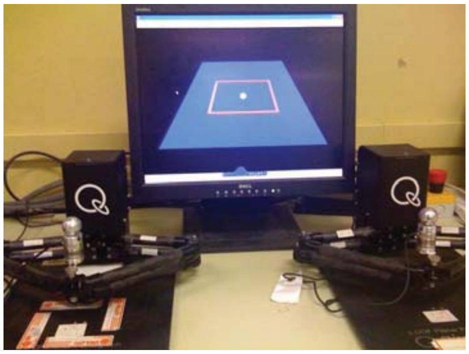


Fig. 3. Picture of the collaborative haptic training experimental setup.

(a) (b)

Fig. 4. Environment viewpoint in the square following task: (a) top view, (b) front view.

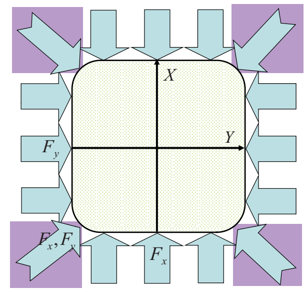
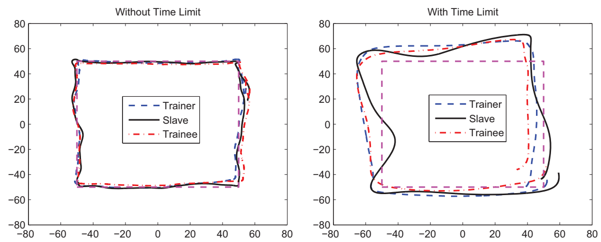


Fig. 5. Force field around the square trajectory as the virtual fixtures.



(a) (b)

Fig. 6. Square path following experiment with subject 3 when the slave robot is in free motion and environment is viewed from the top at $\alpha = 0.5$: (a) without time limit, (b) with time limit.

ii. The slave robot moves in a mushy environment. The mushiness is represented by pure constant linear damping effect across the environment, resembling a real environment with damping coefficient of 2 $Nsec/m$.

iii. The slave robot moves in an environment with virtual fixtures. Virtual fixtures are a penalty-based form of haptic assistance, dependent on the slave's position within the virtual environment [11]. When the user moves to a forbidden region of the workspace, corrective feedback represented with a forcefield around the workspace, push the haptic device, held by the user, back to an acceptable position. Figure 5 shows the desired path and the force field around it. For our experiment we have implemented the virtual fixture in the form of pure stiffness with stiffness 500 N/m.

3) Dominance Factor: The dominance factor is set by the trainer in the order of $\alpha = 1, 0.75, 0.5, 0.25, 0$, signifying a shift of dominance from the trainer to the trainee.

4) Subjects: Five subjects, three males and two females, have been selected as trainees, while the trainer remain the same for all experiments. During the tests, the trainer uses his articulated hand (right hand), however the trainee uses the less articulated hand (left hand). This privilege grants trainer with an extra skill and dexterity that a trainer needs when interacting with trainees.

Each subject is examined for 4 environment types (free motion/top view, free motion/front view, mushy environment/front view, and environment with virtual fixtures/front view). Each experiment is tried for 5 dominance factors. For each dominance factor 8 trials consisting of two square path loops are tried. Overall, 160 experiments (4 environments/viewpoints, 5 dominance factors, 8 trials) have been carried out by each subject.

Note that in the above experiments, there is no time limit to accomplish the task. If the time is limited, then the performance of the trainees will be affected for worse up to a point that they cannot perform to their maximum capabilities. Figure 6 shows a single loop of the trajectory following experiment with subject 3 at $\alpha = 0.5$ when the slave robot is in free motion and the environment is viewed from the top. There is no time limit in the result shown in Figure 6(a) and the task is accomplished in 9 seconds. However, if there is a time limit of 5 seconds, the trajectory following is degraded as shown in Figure 6(b). Comparison between these two figures shows that task completion time has significant effect on the performance of the users. Therefore, in our user studies there is no time limit. On the experiments, however, the users are expected to finish the task in reasonable amount of time.

In the next section we will introduce a number of performance indices and assess the performance of the users in the above experiments.

IV. Performance Evaluation

In this section, the performance of the dual-user haptic system with the transparency-optimized controller [10] is experimentally evaluated for the above specific square path following task.

A. Task-oriented Performance Measures

Task completion time, accuracy of the traversed trajectory, and the amount of exchanged energy between the trainer and the trainee, are three measures of performance utilized in this paper.

1) Task Completion time: Task completion time is the time that it takes for the slave to traverse two loops of the square path. Since each experiment is carried out eight times for each α in each operating condition, the average of task completion time is computed over the 8 trials.

2) Error-based Performance Index: Figure 7 shows the workspace of the Pantograph for the square path following task. The slave robot should move on the black solid square. To calculate the error, depending on the position of the robot end-point, denoted by (P_x, P_y), in any of the areas 1 to 5, the tracking error is derived from

$$e = \begin{cases} |b - P_y| & area1 \\ |a - P_x| & area2 \\ |-b - P_y| & area3 \\ |-a - P_x| & area4 \\ e_d & area5 \end{cases} \tag{6}$$

Here $a = b = 50\,mm$, and e_d are the Euclidean distance between the robot's position and the corresponding desired square path corner in area 5. The dash line inner square in Figure 7 specifies the borders between different areas within the square. The size of the inner square is selected such that the horizontal and vertical distance between the two squares is $2\,mm$. To quantify training performance for the above path following tasks over time and distance, the following performance index is defined:

$$J_{error}(\alpha) = \frac{\frac{1}{n}\sum_{n}^{i=1} e_i}{l} \tag{7}$$

where e_i is the spatial error at each sample point i, l is the length of the traversed path by the robot end-effector, and n is the number of samples. The cost function $J_{error}(\alpha)$ is calculated after each trial for each α. Since each experiment is carried out eight times for each α in each operating condition, the average value of $J_{error}(\alpha)$ is computed over the 8 trials. In this definition, the accuracy of the task has priority over the time required to accomplish the task.

3) Energy-based Performance Index: The energy-based performance indices are defined as:

$$J_{x_{energy}}(\alpha) = \frac{1}{n-1}\sum_{n}^{i=1} f_{x_i}(P_{x_{i+1}} - P_{x_i}) \tag{8}$$

$$J_{y_{energy}}(\alpha) = \frac{1}{n-1}\sum_{n}^{i=1} f_{y_i}(P_{y_{i+1}} - P_{y_i}) \tag{9}$$

where f_{x_i} and f_{y_i} are the applied forces to the robot end-effector in x and y directions, respectively. This performance

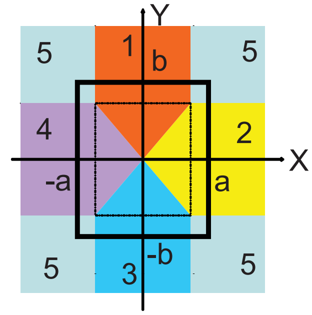


Fig. 7. Workspace of the Planar Twin Pantograph in the square following task.

index measures the amount of energy that each user spends to accomplish the task. $J_{x_{energy}}(\alpha)$ and $J_{y_{energy}}(\alpha)$ are calculated after each trial for each α. The total energy is then calculated as:

$$J_{energy}(\alpha) = J_{x_{energy}}(\alpha) + J_{y_{energy}}(\alpha) \tag{10}$$

and for each α the average value of $J_{energy}(\alpha)$ over the eight trials is calculated.

B. Performance Assessment

1) Task Completion Time: Figure 8 shows the performance of five subjects in terms of time averaged over 8 trials for different α's under various operating conditions. As it can be seen from the figure, adding virtual fixtures to the environment and changing the environment viewpoint from top to front reduces the task completion time. In most of the cases (not for subject 4), the environment mushiness helps the subjects finish the task sooner. There does not seems to be a correlation between the dominance factor and the task completion time.

2) Error-based Performance: Figure 9 shows the average error-based performance index, $J_{error}(\alpha)$, for the slave robot for five subjects. The index is calculated for five different dominance factors and then averaged over the eight trials for each α for all the experiment conditions. The results show that giving full authority to trainer or trainee always results in better performance. As it can be seen from Figure 9, in most of the cases changing α from 0.75 to 1 decreases the performance index implying better performance. This is also true for trainee by changing α from 0.25 to 0. The results show that for all subjects, $J_{error}(1) \leq J_{error}(0)$ validates the assumption that the trainer using articulated arm has higher maneuverability skill than the trainee that uses the less articulated arm. Experiments with subject 4 shows that when the trainee is given authority, $J_{error}(\alpha)$ increases which indicates the poor performance of the trainee. This trend can also be seen from the other subjects experiments but not necessarily for the mid values of α. Figure 9 shows that adding virtual fixtures to the environment result in poor performance. This is because the users make the slave robot penetrate

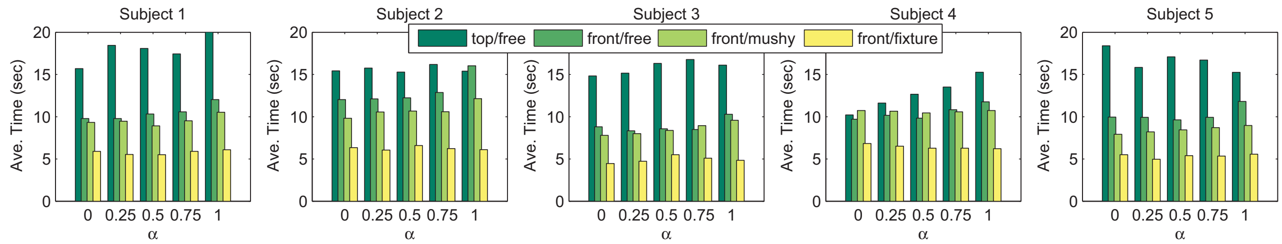


Fig. 8. Performance of five subjects in terms of time for different α's under various operating conditions: i) top view in free motion, ii) front view in free motion, iii) front view in mushy environment, iv) front view with virtual fixtures.

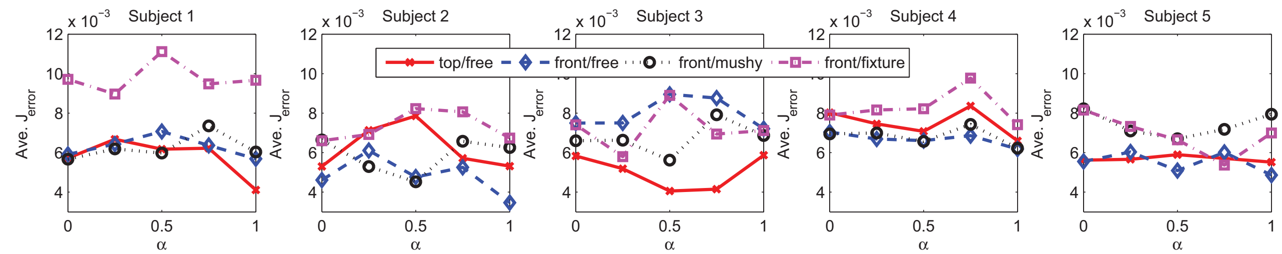


Fig. 9. Spatial performance index, $J_{error}(\alpha)$, of five subjects averaged over the eight trials for the square following task for different α's under different operating conditions: i) top view in free motion, ii) front view in free motion, iii) front view in mushy environment, iv) front view with virtual fixtures.

into the environment until the users feel the virtual walls, therefore creating a constant error all over the traversed path.

3) Energy-based Performance: Figure 10 shows the energy-based performance index, $J_{energy}(\alpha)$, for two subjects (subject 1 and 2) averaged over the eight trials under different operating conditions for all 5 values of dominance factor for the trainer (Figure 10(a)) and the trainees (Figure 10(b)). As it can be seen from the figure, changing the environment from free motion, to mushy, to virtual fixtures increase the amount of energy users spent on performing the task. This is because the forces that are generated in the environment increases. The same trend is observed from the experiments with other subjects. It is also noticeable that the trainer spent less amount of energy than the trainee to perform the task in almost all operating conditions.

V. Discussion

A. Statistical Analysis: Effect of Environment and Dominance Factor

A repeated measure two-way analysis of variance (ANOVA) was carried out to investigate the significance of the environment and the dominance factor on the error-based and the energy-based performances. The two factors have been considered as the five α's (1, 0.75, 0.5, 0.25 and 0) and the four environments (top view/free motion, front view/free motion, front view/mushy environment, front view/virtual fixtures). The ANOVA results show that the effect of dominance factor is not significant on both performance indices. However, the effect of environment is significant ($P \cong 0$ for all performance indices). The two-way interaction analysis shows that there is no evidence of a synergistic effect of the two factors on the spatial ($P = 0.76$) and on the energy-based ($P = 0.99$ for trainer and $P = 1$ for trainee) performances. Therefore, in the following, a discussion about the environment effect on subjects performance is presented.

B. Effect of Environment

1) Effect of Environment viewpoint: Changing the environment viewpoint in square following task from top to front decreases the task completion time (Figure 8). This change increases the amount of energy the users spent on performing the task (Figure 10). However, in terms of spatial performance this change results in better performance for subject 2 and 4, and worse performance for subjects 1 and 3 (Figure 9).

2) Effect of Environment Mushiness: Changing the environment from free motion to mushy environment results in reduce task completion time (see Figure 8) and more energy spent by both trainer and trainee (see Figure 10). This is because the users can move the robot faster in mushy environment without deviating much from the actual path. However, the environment forces build up as the robot moves faster resulting in more energy spent by the users.

3) Effect of Virtual Fixtures: From Figure 10, it can be observed that adding virtual fixture increases the amount of exchanged energy by users compared to other operating conditions. However, task completion time reduces significantly (Figure 8). This is because of the support provide by virtual walls that prevent users from deviating from the actual path. This is at the cost of spending more energy to penetrate into the environment and

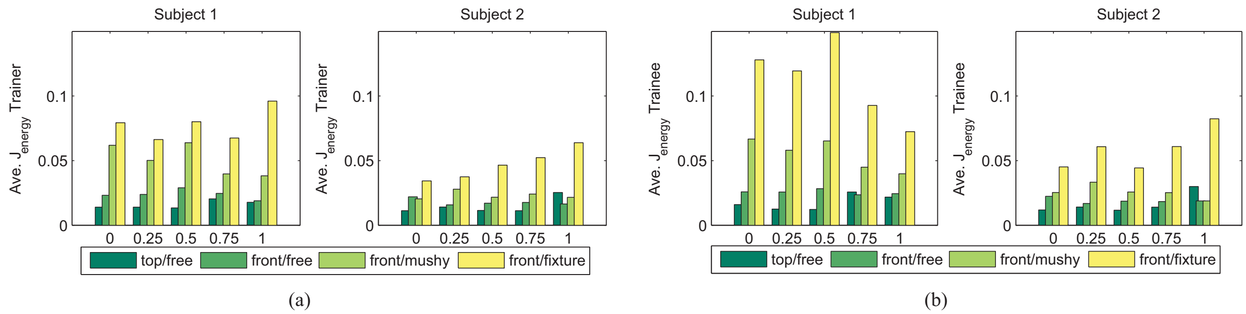


Fig. 10. Energy performance index, $J_{energy}(\alpha)$, of two subjects averaged over the eight trials for the square following task for different α's under different operating conditions: i) top view in free motion, ii) front view in free motion, iii) front view in mushy environment, iv) front view with virtual fixtures.

lean on the virtual walls.

C. Trade off between Task Completion Time and Path Following Performance

Figure 8 shows that the experiment with subject 3 on following the square path with the top view environment was relatively a slow experiment (more than 15 seconds) in comparison with the other operating conditions (less than 10 seconds) for the same subject. However, by looking at the error-based performance of the experiment with subject 3 in Figure 9, one can see that the path is traversed with the least error when the environment was viewed from the top which was at the cost of spending more time.

VI. Conclusions and Future Works

In this paper, a multilateral shared control architecture has been proposed and implemented on a dual-user haptic simulation testbed. The performance of the proposed collaborative haptic controller has been experimentally evaluated for a specific task of following a square path.

To measure the performance we have used task completion time and introduced two spatial and energy-based performance indices. Our user study investigated the effect of environment point of view, mushiness in the environment, and the existence of virtual fixtures on human haptic guidance for a square path following task.

The studies have revealed that as the authority over the task is transferred to the trainer, he/she will have a better performance in terms of lower error in trajectory following. Changing the environment point of view from top to front or adding damping to the environment decreases the task completion time at the cost of spending more energy. Virtual fixtures make the users apply more energy to complete the task, however it significantly reduces the amount of time needed to complete the task.

Future work will focus on performance evaluation in following other shapes of tasks such as circle and trajectories that more resemble a surgical tool path during simple operations such as suturing. For these applications, task completion time and energy-based methods are more suitable assessment methods as there is no reference trajectory that the slave trajectory can be compared to in the error-based method.

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