Enhancing Robotic Telesurgery with Sensorless Haptic Feedback

Nural Yilmaz[1,2*], Brendan Burkhart[1], Anton Deguet[1], Peter Kazanzides[1], Ugur Tumerdem[1,2]

[1*]Department of Computer Science, Johns Hopkins University, Baltimore, 21218, MD, USA.
[2*]Department of Mechanical Engineering, Marmara University, Istanbul, 34854, Turkey.

*Corresponding author(s). E-mail(s): nyilmaz2@jhu.edu;
Contributing authors: bburkha4@jhu.edu; anton.deguet@jhu.edu; pkaz@jhu.edu; ugur@jhu.edu;

Abstract

Purpose: This paper evaluates user performance in telesurgical tasks with the da Vinci Research Kit (dVRK), comparing unilateral teleoperation, bilateral teleoperation with force sensors and sensorless force estimation.
Methods: A four channel teleoperation system with disturbance observers and sensorless force estimation with learning based dynamic compensation was developed. Palpation experiments were conducted with 12 users who tried to locate tumors hidden in tissue phantoms with their fingers or through handheld or teleoperated laparoscopic instruments with visual, force sensor, or sensorless force estimation feedback. In a peg transfer experiment with 10 users, the contribution of sensorless haptic feedback with/without learning based dynamic compensation was assessed using NASA TLX surveys, measured free motion speeds and forces, environment interaction forces as well as experiment completion times.
Results: The first study showed a 30% increase in accuracy in detecting tumors with sensorless haptic feedback over visual feedback with only a 5-10% drop in accuracy when compared with sensor feedback or direct instrument contact. The second study showed that sensorless feedback can help reduce interaction forces due to incidental contacts by about 3 times compared with unilateral teleoperation. The cost is an increase in free motion forces and physical effort. We show that it is possible to improve this with dynamic compensation.

Conclusion: We demonstrate the benefits of sensorless haptic feedback in teleoperated surgery systems, especially with dynamic compensation, and that it can improve surgical performance without hardware modifications.

Keywords: Teleoperation, force sensing, haptics, deep learning

1 Introduction

The da Vinci Surgical System (Intuitive Surgical, Sunnyvale, USA) is widely used for minimally-invasive surgical procedures. It follows a telesurgery approach, where the surgeon sits at a console, viewing images from a stereo endoscope and remotely controlling dexterous instruments, where the endoscope and instruments are inserted into the patient body through small incisions. While the system provides excellent stereo visualization, one frequent criticism is the lack of force (haptic) feedback to the surgeon. Haptic feedback plays a crucial role in surgical procedures as it helps surgeons assess the properties of different types of tissue and avoid application of excessive force that could damage tissue or surgical tools. It is, however, challenging to integrate a force sensor into the instruments, given constraints on the size, cost and electrical connectivity, as well as the requirement for sterility. Researchers have used external force sensors in the lab environment to assess the contribution of haptic feedback in robotic surgery systems [1–3], however, these methods cannot be directly implemented in the surgical theater.

In our prior work [4–8], we investigated methods for estimating the external force based on existing sensor feedback, which includes motor positions, velocities and torques. This was implemented on the da Vinci Research Kit (dVRK) [9, 10], an open research platform based on the first-generation da Vinci Surgical System. Other investigators have demonstrated this capability for the dVRK, also using the existing motor feedback signals [11–13] or in combination with video feedback [14, 15]. However, although these methods can provide an estimated force/torque (wrench), they are not as accurate as an actual force sensor or do not convey the force to the user in all the available degrees-of-freedom.

The purpose of this work is to experimentally evaluate whether our most recent force estimation method [8] can provide sufficient accuracy for a representative surgical task, specifically tissue palpation. However, this also requires a method to convey the estimated force to the surgeon. Haptic feedback is the most obvious choice, but has been challenging to implement on the dVRK due to lack of a low-level bilateral teleoperation framework, and the difficulty in implementing bilateral teleoperation at higher levels of control, especially due to lower control frequencies and higher latencies. As a result, some researchers have adopted commercial haptic devices, such as the Sigma.7 haptic interface (Force Dimension, Nyon, Switzerland) [16], to replace the dVRK Master Tool Manipulators (MTMs). In this work, we take advantage of a recently-developed four-channel bilateral teleoperation architecture for the dVRK [17], summarized in Section 2.1, to convey these forces via haptic feedback in all available

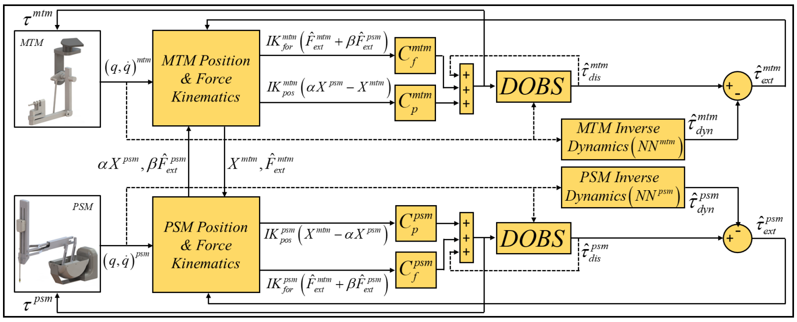

Fig. 1: Control Architecture. q: position, $\dot{q}$: velocity, X, F: Cartesian position and force, τ: actuator force/torque, α, β: motion and force scale factors, IK: position/force inverse kinematics, $C_{p/f}$: position/force controllers, $DOBS$: disturbance observer

degrees of freedom. Other methods employ sensory substitution by conveying the forces via visual overlays [1, 18, 19], auditory [1, 20], tactile [21] or vibrotactile [20] feedback.

Section 2.2 describes the experimental setup for the user study, where subjects palpated a phantom, under four different teleoperation conditions, to identify an embedded object with higher stiffness: unilateral teleoperation, bilateral teleoperation using estimated forces without/with compensation of dynamic forces, and bilateral teleoperation using a force sensor embedded in the phantom. In addition, the subjects palpated under two non-teleoperated conditions: with a bare hand, and while holding the dVRK instrument. We then performed a second user study, using a peg transfer task, to evaluate the "feel" of the different conditions for a task that also requires a significant amount of free space motion. Results for both user studies are presented in Section 3. The results indicate that the best teleoperated performance is achieved with the force sensor, but the two conditions using estimated force perform nearly as well. The palpation result did not show a significant difference whether or not dynamic forces were compensated, but the peg transfer task indicates that compensation of dynamic forces leads to a lighter "feel" of the MTM, as expected, though it is not as light as the unilateral teleoperation condition. This study also shows that sensorless haptic feedback can help to significantly reduce interaction forces with the surgical environment, which can be dangerously high in unilateral teleoperation.

2 Method

2.1 Control System

Figure 1 provides a block diagram of the proposed teleoperation system [17]. The robot dynamics is based on the Euler-Lagrange model, which can be written as:

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}}) + \mathbf{G}(\mathbf{q}) + \mathbf{F}(\dot{\mathbf{q}}) = \boldsymbol{\tau} \tag{1}$$

where $\mathbf{q}, \dot{\mathbf{q}}$ are the joint position/velocity vectors, $\boldsymbol{\tau}$ is the joint torque vector, $\mathbf{M}(\mathbf{q})$ is the inertia matrix, $\mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})$ is the Coriolis and centrifugal torque vector, $\mathbf{G}(\mathbf{q})$ is the gravity vector, and $\mathbf{F}(\dot{\mathbf{q}})$ is the friction vector. Disturbance observer based acceleration control can be used for feedback linearization and has equivalent stability properties to passivity based controllers without the need for exact models [17]. For disturbance observer based acceleration control [22], the dynamics in actuator space can be written as the sum of the nominal actuator dynamics and disturbances acting on the actuators:

$$\mathbf{M_n}\ddot{\mathbf{q}} + \underbrace{\boldsymbol{\tau_{frc}} + \boldsymbol{\tau_{int}} + \boldsymbol{\tau_{ext}}}_{\boldsymbol{\tau_{dis}}} = \boldsymbol{\tau} \tag{2}$$

where $\mathbf{M_n}$ is the nominal model motor inertia, $\tau_{\mathbf{dis}}$ is the lumped disturbance acting on the actuator, $\tau_{\mathbf{int}}$ is the sum of internal robot forces/torques: $\tau_{\mathbf{int}} = (\mathbf{M}(\mathbf{q}) - \mathbf{M_n})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}}) + \mathbf{G}(\mathbf{q})$, $\tau_{\mathbf{frc}}$ is the friction force/torque and $\tau_{\mathbf{ext}}$ is the sum of all the external forces/torques acting on the actuator. A disturbance observer (DOBS in Fig. 1) estimates the disturbances acting on each actuator with the following equation:

$$\hat{\tau}_{dis} = \frac{g_{dis}}{s + g_{dis}}(\tau + g_{dis}M_n\dot{q}) - g_{dis}M_n\dot{q} \tag{3}$$

where g_{dis} is the cut-off frequency of a low pass filter. An acceleration control system with an acceleration reference $\ddot{q}_{ref}$ and reference (desired) torque τ_{ref} can be written with a disturbance observer as:

$$\tau_{ref} = M_n\ddot{q}_{ref} \tag{4}$$

$$\tau = \tau_{ref} + \hat{\tau}_{dis} \tag{5}$$

It can be shown that this controller compensates the disturbances within the observer bandwidth g_{dis} and forces the robot dynamics to the nominal actuator dynamics [22].

The disturbance observer (DOBS) can also estimate external forces [4, 8]. Both the dVRK Master Tool Manipulator (MTM) and Patient Side Manipulator (PSM) have complex mechanisms, including elastic transmissions and spring loading which is challenging to model accurately with parametric identification, so we consider them as a part of $\tau_{\mathbf{int}}$ in (2). To estimate $\tau_{\mathbf{ext}}$ from disturbance estimates in (3), we identify robot dynamics (i.e., the "inverse dynamics" blocks in Fig. 1) using deep learning. Deep learning was selected due to difficulties in modeling surgical robots and the ease of transfer learning for different surgical scenarios. Two neural networks are used for each robot, with each network responsible for identifying three degrees of freedom corresponding to the positioning and wrist axes in actuator space. Each network has an input layer with 6 inputs that are the actuator positions and velocities. To extract important information from time-series data, we use an LSTM layer. The output of the LSTM layer, which consists of 256 hidden units, is then fed into 3 fully connected (FC) layers with ReLU activation functions. The FC layers have 256, 128 and 64 hidden neurons. The output regression layer produces 3 joint disturbance torque estimates. The network architecture was developed in our previous works on force estimation and its selection and hyperparameter tuning was explained in more detail in [8]. Training data was collected for identification purposes by having each robot bilaterally teleoperate the other in free space. The data collection lasted for about 5 minutes at around 1 kHz sampling rate and 20% of the data was set aside for validation with the rest designated for training. We utilized an NVIDIA Quadro P1000 GPU and the Adam optimizer to train our models in 25 epochs.

We train our networks with disturbance estimates $\hat{\tau}_{\mathbf{dis}}$ in free motion by collecting joint position, velocity and disturbances. The output of the neural networks (NN) predicts the disturbances acting on the joints when the robot is in free motion $\mathbf{NN}(\mathbf{q}, \dot{\mathbf{q}}) = \hat{\tau}_{\mathbf{dyn}} \approx \tau_{\mathbf{int}} + \tau_{\mathbf{frc}}$.

During contact and in the presence of an external torque on the actuators, the identified torque/disturbance can be subtracted from the disturbance estimate $\hat{\tau}_{\mathbf{dis}}$ [23] to obtain the external torque estimate:

$$\hat{\tau}_{\mathbf{ext}} = \hat{\tau}_{\mathbf{dis}} - \mathbf{NN}(\mathbf{q}, \dot{\mathbf{q}}) \tag{6}$$

The external forces in Cartesian space can then be obtained by applying the pseudo-inverse Jacobian transpose $\mathbf{J^{-T}}$:

$$\hat{\mathbf{F}}_{\mathbf{ext}} = \mathbf{J^{-T}} \hat{\tau}_{\mathbf{ext}} \tag{7}$$

It was shown in [24] that to achieve ideal bilateral teleoperator transparency and perfect kinesthetic coupling between the operator and the environment it is required to exchange both position and force measurements between the robots. Since we can estimate the forces on both the MTM and the PSM, it has become possible to implement the four channel teleoperation architecture on the dVRK. The controller goals in Cartesian space with motion scaling, which is required in robotic surgery, can be written as $\mathbf{X^{mtm}} = \alpha \mathbf{X^{psm}}$ and $\hat{\mathbf{F}}^{\mathbf{mtm}}_{\mathbf{ext}} = -\beta \hat{\mathbf{F}}^{\mathbf{psm}}_{\mathbf{ext}}$, where $\mathbf{X}$ represents the Cartesian position vector, $\hat{\mathbf{F}}_{\mathbf{ext}}$ are the Cartesian external force estimates, and α, β are the scaling factors between MTM and PSM positions and forces.

To realize the four channel control architecture, acceleration references for acceleration controllers in actuator space can be written as (and shown in Fig. 1):

$$\begin{aligned} \mathbf{M_n} \ddot{\mathbf{q}}^{\mathbf{mtm}}_{\mathbf{ref}} &= \mathbf{C^{mtm}_p} \mathbf{IK^{mtm}_{pos}} \left(\alpha \mathbf{X^{psm}} - \mathbf{X^{mtm}} \right) - \mathbf{C^{mtm}_f} \mathbf{IK^{mtm}_{for}} \left(\hat{\mathbf{F}}^{\mathbf{mtm}}_{\mathbf{ext}} + \beta \hat{\mathbf{F}}^{\mathbf{psm}}_{\mathbf{ext}} \right) \\ \mathbf{M_n} \ddot{\mathbf{q}}^{\mathbf{psm}}_{\mathbf{ref}} &= \mathbf{C^{psm}_p} \mathbf{IK^{psm}_{pos}} \left(\mathbf{X^{mtm}} - \alpha \mathbf{X^{psm}} \right) - \mathbf{C^{psm}_f} \mathbf{IK^{psm}_{for}} \left(\hat{\mathbf{F}}^{\mathbf{mtm}}_{\mathbf{ext}} + \beta \hat{\mathbf{F}}^{\mathbf{psm}}_{\mathbf{ext}} \right) \end{aligned} \tag{8}$$

where $\mathbf{C_p} = \mathbf{k_p} + \mathbf{k_d s}$ is a PD position controller and $\mathbf{C_f}$ is a proportional force controller, and $\mathbf{IK_{pos}}, \mathbf{IK_{for}}$ are position and force inverse kinematics functions for the MTM and PSM robots. Kinematics include the registration between the robots and the coupling matrices between the actuators and the robot joints. The controller is written in the form (8) for the sake of presentation, whereas in practice the actuator position measurements $\mathbf{q^{mtm}}, \mathbf{q^{psm}}$ and actuator external torque estimates $\hat{\tau}^{\mathbf{mtm}}_{\mathbf{ext}}, \hat{\tau}^{\mathbf{psm}}_{\mathbf{ext}}$ are used instead of $\mathbf{IK^{mtm}_{pos}}(\mathbf{X^{mtm}}), \mathbf{IK^{psm}_{pos}}(\mathbf{X^{psm}})$ and $\mathbf{IK^{mtm}_{force}}(\hat{\mathbf{F}}^{\mathbf{mtm}}_{\mathbf{ext}}), \mathbf{IK^{psm}_{for}}(\hat{\mathbf{F}}^{\mathbf{psm}}_{\mathbf{ext}})$.

With the disturbance observer, the controller torque for each joint of the robots can then be computed as $\tau^{\mathbf{mtm}} = \mathbf{M_n} \ddot{\mathbf{q}}^{\mathbf{mtm}}_{\mathbf{ref}} + \hat{\tau}^{\mathbf{mtm}}_{\mathbf{dis}}$ and $\tau^{\mathbf{psm}} = \alpha \mathbf{M_n} \ddot{\mathbf{q}}^{\mathbf{psm}}_{\mathbf{ref}} + \hat{\tau}^{\mathbf{psm}}_{\mathbf{dis}}$.

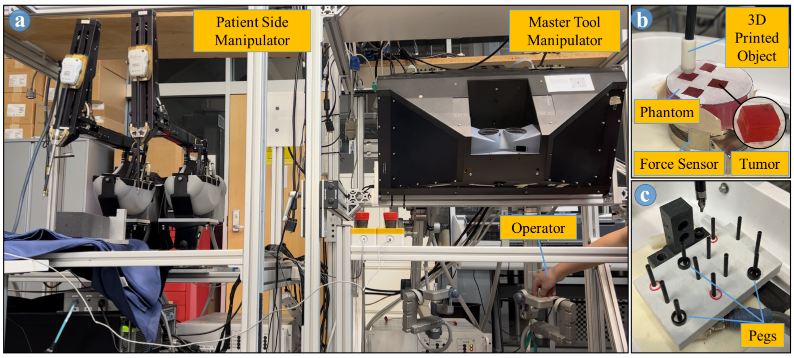

Fig. 2: (a) PSM and MTM robots, (b) Palpation and (c) Peg transfer setups

While the four channel teleoperation system can in theory provide ideal transparency, in practice there is always operationality [25] which can be described as the added force feedback to the operator especially in free motion, due to robot dynamics and control system latency.

2.2 Experiment Design

For the experiments, we used unmodified first-generation dVRK MTM and PSM robots, as shown in Fig. 2. The control system was developed using C++ and has been integrated into the dVRK software stack and made accessible to the dVRK community. The controller parameters used in the experiments are given in Table 1.

The digital controller without neural networks can run at a sampling rate of 1.5 kHz. However, due to limitations in the processing capabilities of the computer hardware, the use of neural networks necessitated a reduction in the sampling rate to 1 kHz. The control system latency between the dVRK robots was observed to vary between 1.27 and 3.48 milliseconds.

Although the dVRK PSM and MTM robots have 7 and 8 degrees of freedom respectively, the proposed bilateral teleoperation system is implemented in 6 degrees of freedom. The MTM gripper, by design, has an encoder and no actuator and can only be used to control the PSM gripper unilaterally. Additionally, the redundant fourth joint of the MTM was locked to simplify the kinematics for force estimation.

For our first user study, we produced plastisol tissue phantoms (TiP) with different stiffnesses by adding plastisol softener, hardener and dyes. TiPs had the same volume with the following composition, TiP1: 100 mL plastisol + 50 mL softener, TiP2: 125 mL plastisol + 25 mL softener, TiP3: 150 mL plastisol, TiP4: 100 mL plastisol + 50 mL hardener. The Tumor Phantoms (TuP) were cut in cubes and embedded in the TiPs. The TuP composition was 100 mL plastisol + 100 mL hardener. A 3D printed plastic instrument cover was used to prevent piercing of the phantoms. For the second user study we used a peg board and rubber pegs. In both experiments, the users did not use the dVRK stereovision system and had a direct side view of the operation area. In addition, a force sensor (Gamma F/T Sensor, ATI Industrial Automation, Apex, NC, USA) was placed under the phantoms and peg board.

Table 1: Controller parameters used in the control system

	PSM						MTM						Units
i	**1**	**2**	**3**	**4**	**5**	**6**	**1**	**2**	**3**	**5**	**6**	**7**	-
k_p	20	20	800	1.5	1.5	1.5	40	40	40	0.7	0.06	0.05	-
k_d	4	4	56.6	0.05	0.05	0.05	5	5	5	0.05	0.03	0.0016	-
C_f	1	1	1	0.4	0.4	0.4	1	1	1	0.4	0.4	0.4	-
g_f	10	10	10	3	3	3	10	10	10	3	3	3	rad/s
M_n	1e-3	1e-3	1e-3	5e-6	5e-6	5e-6	1e-3	1e-3	1e-3	5e-6	5e-6	5e-6	$kg.m^2$, kg

3 Results

3.1 User Study 1: Palpation for Tumor Detection

Palpation experiments were conducted with 12 individuals to test various teleoperation systems. Participants were selected from Johns Hopkins faculty and students with no vision or hand related disabilities. Gender or age was not a selection criterion, and there were 11 male participants and 1 female participant between 20 and 62 years old with a mean age of 32. In terms of experience with the da Vinci Research Kit (dVRK), the study achieved an even distribution of participants, with half experienced and half inexperienced. In the experiments, 4 TiPs were used. Four points were marked on each TiP and one point included the TuP. These points were covered with tape to prevent visual detection. Users were requested to palpate these points 4-5 times and reported under which point they felt a stiff tumor. Two different motion scalings were tested in the experiments: 1:1 scaling with $\alpha = 1$ and 1:5 scaling with $\alpha = 5$ which corresponds to 5× smaller PSM motions. With each scaling, unilateral teleoperation (Uni), sensorless bilateral teleoperation with (Dyn) and without (nDyn) a dynamic model, and bilateral teleoperation with sensor feedback (FS) was implemented. Users received verbal instructions for the experiments and inexperienced users were given a brief training to operate the system. Users were also asked to palpate with their hand (Hand) and holding the instrument in their hand (Inst). The order with which the users tested different TiPs and controllers was randomized to remove the learning effect. They tested the phantoms with their hand and the hand-held instrument at the end of their sets. Tumor detection accuracy for the different cases is provided in Table 2 and Table 3 provides results from pairwise statistical significance analysis between different test groups using the Wilcoxon rank-sum test. Hand palpation was significantly better than all methods except the instrument. The users were able to detect tumors with their hands 100% of the time. With the instrument in hand, some users were not able to accurately detect the tumors, especially in the stiffest TiP, and the accuracy rate dropped to 95.83%; however, the difference was not statistically significant. Across both scaling factors, sensorless force estimation with or without the dynamic model performed similarly with force sensor feedback, with no statistically significant difference between them. With sensorless haptic feedback (both Dyn and nDyn), accuracy was above 85% and this result was within 5% of the results with force sensor feedback and 10% of direct instrument contact. With unilateral teleoperation, the detection accuracy showed a strongly significant drop (with p-values ≈0.01 or less) to 54.17%, although the users were able to see how far the instrument travelled in the TiP. Scaling did not contribute significantly to tumor detection performance. No significant difference was observed between experienced and inexperienced users.

Table 2: Average and standard deviations of correct answers in the palpation experiment (%).

			SCALING 1:1				**SCALING 1:5**			
	Hand	**Inst**	**Uni**	**nDyn**	**Dyn**	**FS**	**Uni**	**nDyn**	**Dyn**	**FS**
AVG	100.00	95.83	54.17	85.42	85.42	89.58	58.33	85.42	87.50	87.50
STD	0.00	9.73	29.84	16.71	12.87	16.71	19.46	16.71	13.06	16.85

Table 3: Statistical significance between different groups as indicated by p-values for user study 1. Upward arrows (↑) show that the corresponding row group has a higher mean than the column group with a statistical significance of $p<0.05$, whereas downward arrows (↓) indicate that the row group has a lower mean with a statistical significance of $p<0.05$.

	SCALING 1:1					**SCALING 1:5**				
	Inst	**Uni**	**nDyn**	**Dyn**	**FS**	**Inst**	**Uni**	**nDyn**	**Dyn**	**FS**
Hand	0.166	0.000 ↑	0.007 ↑	0.002 ↑	0.036 ↑	0.166	8e-06 ↑	0.007 ↑	0.006 ↑	0.016 ↑
Inst		0.001 ↑	0.086	0.042 ↑	0.339		6e-05 ↑	0.086	0.097	0.178
Uni			0.011 ↓	0.010 ↓	0.004 ↓			0.003 ↓	0.001 ↓	0.002 ↓
nDyn				0.896	0.488				0.870	0.745
Dyn					0.357					0.869

3.2 User Study 2: Peg Transfer

The peg transfer experiment was conducted with 10 users, who were not surgeons. The users were selected from Johns Hopkins faculty and students with no vision and hand related disabilities. Gender and age were not exclusion criteria, and there were 7 males and 3 females. The ages were between 20-40 with a mean age of 27. Since we did not see a significant difference in the first study, the second study had 8 experienced and 2 inexperienced users. Three different controllers were used: the unilateral teleoperation system (Uni), the bilateral teleoperation system without a dynamic model (nDyn) and with a dynamic model (Dyn). Users were asked to start the experiments from the same point each time and to sequentially move 3 pegs to specified locations.

In this study, we utilized the NASA Task Load Index (TLX) survey [26] to compare and analyze the perceived workload across the three tasks. The TLX survey assesses various dimensions of workload, including mental demand, physical demand, temporal demand, performance, effort and frustration. By examining these dimensions, we evaluated each task.

Fig. 3 shows the average TLX survey results. The users rated their perceptions over a scale of 20 where lower ratings are closer to ideal. The results clearly highlight the advantages of using dynamic models. Using Uni was mentally most demanding for users, and both haptic feedback systems provided a similar level of improvement. nDyn had the highest physical demand due to the increase in operationality whereas Uni and Dyn had similar levels of physical demand. Uni and nDyn had the highest temporal

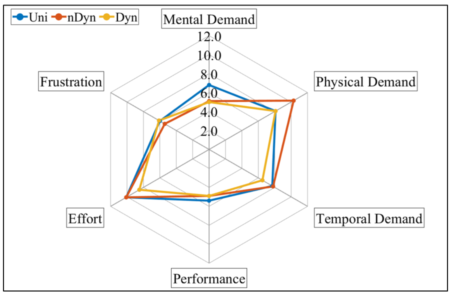

Fig. 3: TLX results comparing the teleoperation systems

demand and the users felt under a similar time pressure whereas Dyn provided an improvement. The controllers with haptic feedback had similar performance ratings and were slightly better than unilateral control. Uni and nDyn required a similar level of effort while Dyn required significantly less effort. All three controllers caused similar levels of frustration, but nDyn had a slight edge over other controllers due to the slower and more predictable behavior of the system. The results showed that introducing haptic feedback can improve mental demand, frustration and performance over unilateral teleoperation but can introduce increased physical demand if dynamic models are not used. Sensorless haptic feedback with dynamic models also improves total effort and temporal demand over unilateral teleoperation, with a similar physical demand. This translates to a significant improvement in physical demand over haptic feedback without dynamic models.

Table 4: Averages (standard deviations) of completion times (s), RMS force sensor measurements (N), peak force sensor measurements (N), RMS free motion MTM force (N) and velocity (mm/s) during Peg Transfer.

Task	Time	RMS(FS)	Peak(FS)	MTM Force	MTM Velocity
Uni	39.20 (16.13)	1.50 (0.81)	9.71 (4.75)	0.37 (0.12)	1.77 (0.45)
nDyn	40.40 (13.99)	0.59 (0.23)	3.52 (1.05)	2.50 (0.29)	2.94 (0.82)
Dyn	38.80 (15.03)	0.57 (0.27)	3.28 (0.90)	1.92 (0.38)	2.91 (0.72)

Table 5: Statistical significance (p-values) for user study 2. Upward arrows (↑) show that the corresponding row group has a higher mean than the column group with a statistical significance of $p<0.05$, whereas downward arrows (↓) indicate that the row group has a lower mean with a statistical significance of $p<0.05$.

	Time		rms(FS)		peak(FS)		mtm Force		mtm Vel	
	nDyn	Dyn	nDyn	Dyn	nDyn	Dyn	nDyn	Dyn	nDyn	Dyn
Uni	0.879	1.000	0.005 ↑	0.003 ↑	0.001 ↑	0.001 ↑	0.000 ↓	0.000 ↓	0.003 ↓	0.003 ↓
nDyn		0.970		0.571		0.678		0.006 ↑		0.850

Table 4 provides objective data from the peg transfer task. Time is the average task completion time, rms(FS) is the average of root mean square force sensor forces from each experiment run and peak(FS) is the average of peak force sensor measurements from each run. MTM Force and Velocity are the average of the estimated RMS MTM

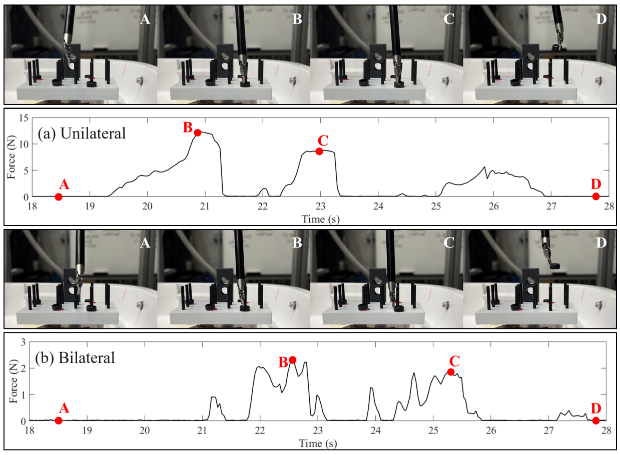

Fig. 4: Sample cases from the peg transfer user studies. Resultant force provided by the force sensor in (a) unilateral (b) bilateral teleoperation.

forces and velocities in Cartesian space. Table 5 provides p-values from the Wilcoxon rank-sum test for statistical significance between the methods. The controllers had very close completion times, with no statistically significant difference. As can be seen from peak and RMS force sensor measurements, both bilateral teleoperation systems displayed significantly smaller contact forces ($p<0.01$) with the peg board when compared with the unilateral teleoperation system which displayed excessive forces. The unilateral teleoperation system, on the other hand, had the best operationality in free motion, with significantly smaller MTM forces. Using dynamic models with bilateral teleoperation significantly improved operationality as can be seen from the MTM forces, however it performed significantly worse than unilateral teleoperation.

Video snapshots and force response plots of two typical 10-second segments from the experiments are presented in Fig. 4 to compare robot response to contact with peg board pins. As can be seen from snapshot C, in unilateral teleoperation the robot applies significant forces and deflects the pin, whereas with haptic feedback (Dyn) there is no deflection visible. Also, the force response plot at B shows a five fold reduction in the interaction forces.

4 Discussion and Conclusions

This study assessed user performance in telesurgical tasks with a sensorless transparency-optimized haptic teleoperation system for the da Vinci Research Kit. The results obtained from our experiments provide valuable insights into the potential of haptic feedback in teleoperated surgery.

Our first set of experiments demonstrated a significant 30% increase in tumor detection accuracy using sensorless haptic feedback over visual feedback only. This increase in accuracy was achieved with only a modest 5-10% drop in accuracy compared to sensor feedback or direct instrument contact. The results suggest that sensorless haptic feedback can significantly enhance a surgeon's ability to assess tissue stiffness, which can be crucial in surgery. While haptic feedback makes the system feel heavier to the user, we show that user effort can be reduced through dynamic compensation techniques. Another key observation from this study is that in unilateral teleoperation, incidental contacts with the peg board pins resulted in extremely high forces (up to 14N) applied to the environment. Use of sensorless haptic feedback with or without dynamic models remedied this situation and provided a three-fold reduction in the interaction forces. This demonstrates that sensorless haptic feedback can also be important for the safety of robotic surgery systems. This feature can also be useful to prevent suture breakage or needle bending. Surgeons who prefer conventional laparoscopy due to haptic feedback can also more easily switch to robotic surgery.

Despite these significant advantages, sensorless feedback introduces increased operationality and physical demand due to the feedback of dynamic forces in free motion. The results we obtained suggest that an increased operationality is an acceptable trade-off for recovering the sense of touch in surgery and the method is ready to be evaluated with further clinical studies. Operationality can also be improved with dynamic models, however a method which can perform closer to unilateral teleoperation is still required. Neural network performance across different users and experiments showed variability as the training was performed in a limited portion of the workspace and with a single user. Changing mechanical configurations, electrical biases and computational load in the dVRK system also contributed to this variability. Because of this, sensorless force estimation without dynamic identification was more consistent and perceived as slightly less frustrating according to the TLX study. To improve consistency and robustness, continuous retraining for each user, with larger workspaces would be required, however this would be impractical. Robust and more generalizable learning approaches for dynamic identification, such as the transfer learning proposed in [8], can be used for clinical implementations to improve reliability and performance. While model based approaches also suffer from variability in the system, the advantage of using neural networks is that performance can be improved with quick retraining using transfer learning without analytical considerations of the surgical setup.

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Conflict of Interest. Nural Yilmaz was supported by the TUBITAK 2214A International Research Fellowship Program. Ugur Tumerdem was supported in part by the Fulbright Visiting Scholar Program and in part by the TUBITAK 2219 Program.

Ethical Approval. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent. Informed consent was obtained from all individual participants included in the study.

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