Sensory Substitution for Force Feedback Recovery: A Perception Experimental Study

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Robotic Assisted Surgeries are commonly used nowadays as a more efficient alternative to traditional surgical options. Both surgeons and patients benefit from those systems as they offer many advantages, including less trauma and blood loss, fewer complications, and better ergonomics. However, a remaining limitation of currently available surgical systems is the lack of force feedback due to the teleoperation setting, which prevents direct interaction with the patient. Once the force information is obtained by either a sensing device or indirectly through vision-based force estimation, a concern arises on *how to transmit this information to the surgeon.* An attractive alternative is sensory substitution, which allows transcoding information from one sensory modality to present it in a different sensory modality. In the current work, we used visual feedback to convey interaction forces to the surgeon. Our overarching goal was to address the question *How should interaction forces be displayed to support efficient comprehension by the surgeon, without interfering with the surgeon's perception and workflow during surgery?* Until now, the use the visual modality for force feedback has not been carefully evaluated. For this reason, we conducted an experimental study with two aims: (1) to demonstrate the potential benefits of using this modality and (2) to understand the surgeons' perceptual preferences. The results derived from our study of 28 surgeons revealed a strong positive acceptance of the users (96%) using this modality. Moreover, we found that in order for surgeons to easily interpret the information, their mental model must be considered, meaning that, the design of the visualizations should fit the perceptual and cognitive abilities of the end user. To our knowledge, this is the first time that these principles are analyzed for exploring sensory substitution in medical robotics. Finally, we provide user-centered recommendations for the design of visual displays for robotic surgical systems.

CCS Concepts: • **Information Interfaces and Presentation → User Interfaces**; *Evaluation/methodology*; • **Models and Principles → User/Machine Systems**; *Human Information Processing*;

Additional Key Words and Phrases: Robotic teleoperation, flow visualization, visualization

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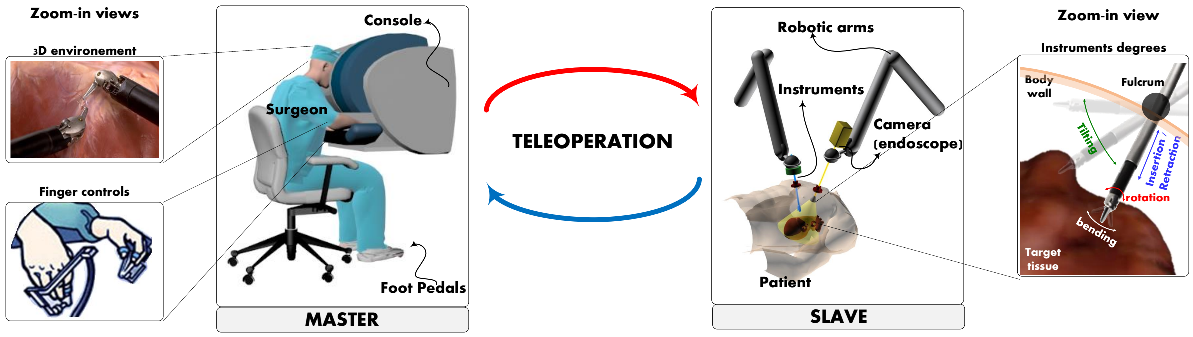

Fig. 1. A typical teleoperated robotic surgical system using a master-slave configuration. At the master side, surgeon is provided with a 3D patient view and is able to perform the procedure using finger controls and foot pedals. All surgeon's actions are reproduced by the slave which holds the surgical instruments.

1 INTRODUCTION

Technological advancements are revolutionizing the field of medicine, by, for example, creating and integrating robotic devices in clinical scenarios such as diagnosis and surgery. In particular, Robotic-Assisted Surgical Systems (RASS) have emerged to tackle the deficiencies associated with traditional open and minimally invasive surgeries [74]. RASS offer distinct advantages for both patients and surgeons. For patients, RASS minimize intra-operative invasiveness, tissue trauma, blood loss, and complication rate, while also reducing post-operative infection risk, pain, scarring, and recovery time. RASS also provide better ergonomics for the surgeons by helping them maintain dexterity, and extending their surgical capabilities by offering optimal hand-eye alignment, motion scaling, and tremor filtering [33, 67].

A robotic surgical system attempts to reproduce the surgeon's motion in a master/slave teleoperated setting. Fig. 1 shows the architecture of one such system. At the master side, the operating surgeon is immersed into a three dimensional environment in which additional useful information can be added to improve transparency in the teleoperated system [49]. Nonetheless, the physical separation between the operating surgeon and the instruments in the operating field leads to complete deprivation of force feedback during surgery.

Even though surgeons are capable of performing procedures without force feedback, the medical robotic community still considers the lack of force feedback a major limitation in currently-available surgical systems. This is because it has been demonstrated that the lack of this feature causes: (1) an increase in errors during the procedure (see e.g. [40, 60, 72]), (2) an increase in mental workload, which can complicate the task at hand and lead to irreversible damages (see e.g. [36, 70]), (3) an increase in task-completion time (see e.g. [48, 70, 72]) and (4) a decrease in surgeon-patient transparency [49]. Moreover, depending on the surgeon's level of expertise and other situational factors, the lack of force feedback can have negative consequences for the surgeon's mental workload and add further complication to the task in hand. This limitation is reputed to be one of the causes that restrict further spread of medical robotics [15].

As it is still an open problem in surgical robotics, researchers have attempted to acquire force information using direct sensing devices. Some of these sensing devices were designed to be placed at the outside of the patient as in [16, 51]. However, force measurement with such a setup is not specific to the tool-tissue interaction region, but is comprised of different forces from the body wall, friction, and the instrument itself. Another placement option for the device is the instrument tip, as in [54, 75], in which the sensor would pass through the insertion port inside the body for a more accurate force measurement. However, this placement enforces strict miniaturization

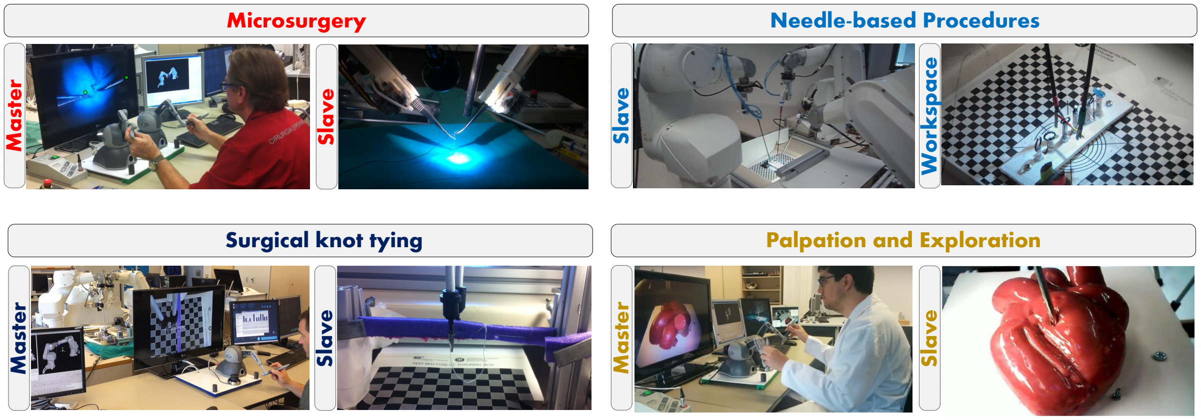

Fig. 2. Surgical tasks where knowing the applied force is relevant and help to decrease the procedure completion time and to avoid injuries.

constraints on the design of the device. Furthermore, any sensing instrument has to satisfy a strict list of medical regulations and restrictions including sterilization, biocompatibility, stability, and robustness [22, 65].

Due to the aforementioned issues, direct force sensing devices have not yet been integrated into current robotic surgical systems. An alternative group of force measuring solutions emerged to overcome these limitations by estimating interaction forces using visual information. The idea behind what is called Vision-Based Force Estimation (VBFE) comes from the conservation principles of continuum mechanics, which point out that the change in shape of an elastic object is directly proportional to the force applied. These kinds of solutions depend on visual information, such as the deformation of tissue under load, to estimate the applied forces. Several authors have demonstrated the benefits of VBFE, for example [3, 20, 29, 45].

Whether it is direct or estimated forces that are available, a natural question arises: *how to provide this information to the surgeon?* Studies show that force feedback information enables surgeons to have better control and precision when manipulating tissue [18, 27]. Moreover, force feedback is especially relevant in the performance of many surgical tasks. For example, in many situations, surgeons perform exploration and palpation tasks in order to identify abnormal or cancerous tissue regions. Having force feedback is helpful in these situations as it enables surgeons to sense tissue mechanical properties and identify specific tissue features that are hard to identify visually. Other surgical tasks involve tissue manipulation, such as dissection and suturing, in which force feedback is important to prevent puncturing the tissue or breaking sutures due to the application of large forces. Fig.2 shows an illustration of these common surgical tasks.

One solution for implementing force feedback would be to transmit the force information to the surgeon's hands using a haptic master device. However, there are many concerns associated with this option, including cost, stability of the controller, degrees of freedom, and space limitations [15, 24, 47]. Moreover, when the gains size is too large, it can result in fatigue for the surgeon, which could consequently affect his/her performance [38].

An attractive alternative to direct force feedback to the surgeon's hands is sensory substitution [4], in which one sense, the sense of touch in this case, is replaced by another sensory modality, vision or audition for example, to convey the lost information indirectly. This option is inspired by theories of perception and mechanisms of brain plasticity, which posit that the brain's complexity allows it to restore certain functions using input from other stimuli or sensory modalities [44, 69]. These theories formed the basis for a variety of studies and conceptual developments involving sensory substitution in teleoperation settings [5, 43, 55, 57].

1.1 Sensory Substitution in Teleoperation

The term *sensory substitution* refers to the ability of the central nervous system to learn a new mode of perception and it has been successfully used for many years to develop sensory aids for people with full or partial deficiency in one or more of their sensory systems [35]. In engineering, this term has come to have a much more general definition than was originally described by Bach-y-Rita [5], and now means simply transcoding information from one sensory modality to present it in a different sensory modality. This is the way we will use the term in the current paper. Since direct force feedback has not yet been integrated into current commercial surgical robotic systems, much of the existing research has investigated using the tactile sensing modality to convey to the surgeon a representation of the forces applied by the robotic tele-manipulators. This offers a significantly more practical solution in RASS settings as it can be easily integrated into existing consoles, is less expensive to implement, and is more stable and manageable/controllable than direct force feedback [47]. Furthermore, sensory substitution can be very effective in training surgeons to use RASS and can compensate for the lack of haptic feedback by the robotic system.

Several studies presented and evaluated different sensory substitution options to transmit forces and tissue properties information. The most commonly used sensory modalities for feedback in this context can be classified into two groups: (i) monomodality including tactile, auditory or vision and (ii) multimodality which refers to the combination of two or more sensory modalities.

1.1.1 Single Sensory Modality (Monomodality). Starting with tactile feedback, early investigations noted that the fingertips contain sensitive sensory receptors that project to relatively large areas in the sensory cortex for information processing, making the vibrotactile modality a good option for presenting force feedback information [39]. The potential benefits of vibrotactile sensory substitution for force feedback were first explored in the work of Massimino and Sheridan, in which they tested the use of tactile and auditory senses to convey forces in teleoperation tasks. In that work, force was scaled to a vibration stimulus presented to the index finger and thumb, and the subjects were required to react as quickly as possible once they recognized the presence of a contact force. The results showed that the operators reacted faster with the vibrotactile feedback than when working with no such feedback.

Researchers in a different study designed a simulated tissue probing task to measure the effect of vibrotactile feedback on surgeons' performance. They measured the effect of this feedback on three main aspects: control of force application, tissue material differentiation, and task completion time [61]. The results showed that vibrotactile feedback allowed subjects to perform better, reducing the depth error and maximum force applied, and achieving more consistency compared to when no vibrotactile feedback was available. Similar results were reported in a more recent study in which authors tested the value of adding vibration feedback to the surgical setup during robotic surgery. The study illustrated that vibration feedback increased the level of awareness about tool contacts and demonstrated a strong user preference for this technology [31]. Despite these benefits, vibrotactile feedback is limited in the amount of information it provides as it is difficult to convey both force direction and magnitude at the same time with vibration. Other drawbacks of vibrotactile feedback start to appear when it is used for long periods of time, as the devices become uncomfortable and the skin starts to lose its sensitivity to the vibration stimuli [6, 31, 46].

Another form of feedback uses the auditory modality, which has been shown to improve task performance in many teleoperation settings. Authors in [30] studied the effect of sensory substitution on suture-manipulation forces. One feedback scenario studied by these authors involved auditory feedback, in which a single tone was provided to the operating surgeon when the applied force reached a specified ideal value. Even though the audio cues did not differentiate forces applied by the left or right-hand instrument, they still improved the consistency of the robotically applied forces. However, surgeons who participated in that study preferred having a continuous/real-time feedback over a discrete/single event information.

This was examined in a different study in which authors presented force feedback as an auditory signal to both ears, with tone loudness being proportional to the magnitude of the force [39]. The results revealed that the reaction speed for recognizing the presence of a contact force was quickest for auditory feedback compared to vibrotactile and traditional force feedback. Even though some studies have shown that continuous frequency-modulated audio feedback is easier to interpret by surgeons, there were still concerns about continual auditory signals being disruptive and confusing in the operating room, as it is already noisy with different sounds coming from medical instruments and verbal communication [70]. Additionally, continuous sounds during long procedures can be a source of discomfort and/or annoyance to the surgeon and might distract communication between assistants and the surgeon [53].

Early investigations showed the feasibility of the visual modality, sight-to-touch, for sensory substitution during delicate surgical tasks. In the work of Bethea et al. [7], surgeons were instructed to perform a robot assisted knot tying task with and without the aid of a color bar sensory substitution. A visual color bar scale was used to convey the mean tension applied to the suture; the bar changed dynamically as the tension increased. The authors found that visual sensory substitution allowed surgeons to have more consistent, precise, and greater control over the tension applied to the fine suture material without breakage.

Visual feedback was also compared against other sensory substitution alternatives in [30], in which the authors presented visual feedback in the form of two bars, one for each hand, in the upper right corner of the display, with the height and color of the bars changing according to the measured force. Out of the different sensory substitution options, visual feedback appeared to enhance most the consistency of applied forces and was superior to the other alternatives. A real-time visual force feedback graphic overlay was presented in [56] during the performance of delicate repetitious robotic manipulation of fine sutures. The graphic overlay in that experiment consisted of two semi-transparent circles superimposed over the corresponding moving instrument tips, which color changed in relation to the force magnitude. Subjects reported a preference for the use of visual feedback as it helped them avoid applying excessive forces and gave them more control over the task.

In a more recent work [41], the authors studied sensory subtraction, which substitutes haptic force with cutaneous stimuli using fingertip skin deformation devices, and compared this method against several other sensory substitution modalities. They reported favorable performance of sensory subtraction and also noted the potential of visual and auditory modalities in medical robotic systems.

1.1.2 Multiple Sensory Modality (Multimodality). Apart from the use of a single sensory modality, multimodal feedback has also been reported in the literature. In [10], authors conducted a meta-analysis to compare the effects of visual-auditory and visual-tactile feedback against the use of visual feedback alone. They reported that multimodal feedback helped improve reaction time, but was not effective in decreasing error rates. The influence of multimodal feedback was also explored in [12], in which the authors suggested that using a combination of modalities can improve realism between the user and the environment, leading to better task performance. In more recent work [68], authors performed a study of all possible combinations between visual, auditory and tactile feedback. They stated that there is no significant difference among them. However, when the visual modality was combined with another modality, users expressed a preference for these combinations, and performance improved when such a combination was offered.

The improved performance of multimodal feedback was further supported by Wickens' multiple resource model [73], which states that human task performance can improve when increased sensory resources are available. However, past work has not fully taken into account the impact of long-duration tasks or the constraints of real surgical task environments. The use of multimodal feedback can be affected in real clinical environments by the attentional capacity of humans, which constrains the amount of information that can be effectively processed [32, 58]. Information loss due to selective attention could lead to increase error during the procedure [8, 13].

1.2 Aim of the Work

Of all abovementioned modalities, we use visual feedback in this work for the following reasons:

- Surgeons who operate the robotic systems primarily rely on their visual system to view and control the remote task via the console monitor. This makes the visual modality a particularly promising sensory substitution option for clinical adoption. Dividing attention between the visual modality and feedback in some other sensory modality could add to the burden on the operator.
- The visual modality allows transmitting continuous spatiotemporal information of the environment over longer periods of time, while minimizing the interference to which the auditory modality is susceptible, and without the reduction in sensitivity that can occur when the tactile modality is used [6, 31, 46, 53].

When vision is used, visualizations representing the information should be integrated in the three dimensional environment displayed to the surgeon. Effective visualization of this information is essential to avoid increasing the surgeon's cognitive workload, something that could otherwise cause fatigue, tissue damage, or increases in the procedure time. Although the visual modality is a feasible and promising option, there still exists the perceptual and cognitive burden of transcoding visual information into the force domain. When attempting to address this issue and develop an effective representation of the information that can be quickly interpreted, several questions naturally arise:

Do all users interpret the different visual representations in the same way? How do users perceive these visualizations? Are they understood correctly? This leads us to formulate a particular question: – How should interaction forces be displayed to support efficient comprehension by the surgeon, without interfering with the surgeon's perception and workflow during surgery?

In this paper and the clinical user study it describes, we offer an extensive discussion of the aforementioned questions with the ***aim of reporting our findings and recommendations on the best options to display force information in an efficient way based on the surgeons' preferences***. We achieve this by testing four visualization systems that use different ways to encode force information using force-to-color mappings and are further explained in the following section. To the best of our knowledge, there are no works that address this issue or analyze how to efficiently represent the information for RASS.

In the remainder of this paper, our perceptual experimental study is structured as follows: Section 2 describes all relevant details about how our clinical study was conducted. In Section 3 we report our findings using statistics and graphical methods, as well as a description of the results from a perceptual and cognitive point of view. Finally, we present the conclusions of the work in Section 4.

2 PERCEPTUAL STUDY

This section describes in detail aspects that are particularly relevant for this study.

2.1 Subjects Description

Twenty eight surgeons, on a voluntary basis, participated in the study. The participants came from four specialties: Obstetrics and gynecology (OB/GYN), Neurosurgery (NS), Pediatric surgery (PDS) and Cardiovascular surgery (CS). This population was divided into two main groups: experts and novices.

What defines participants as experts or novices? This has been a central question in psychology, since we rely on experts to make decisions that affect our environment almost every day. Examples of works that address this question can be seen in [11, 17, 63]. Distinguishing experts from novices depends heavily on individual psychological differences and behavioral characteristics and varies according to the area of study [63].

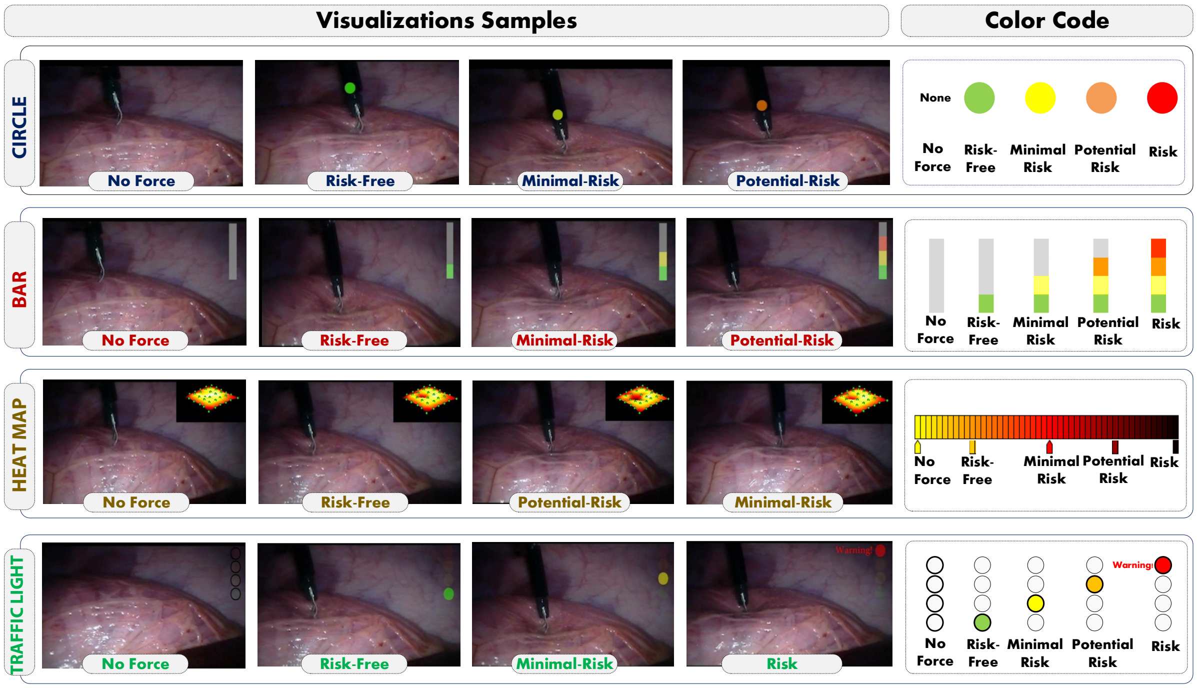

Fig. 3. (From left to right) The four visualizations used in our experiments at different time instants. The coding-color used to indicate the level of risk to the surgeon according to the magnitude of the force applied.

In the medical domain the distinction between experts and novices can be determined based on the number of hours in which surgeons can practice to improve skills such as reduction of task completion time, movement accuracy, and identifying and solving errors [23, 28]. Based on this, we defined the two groups as:

- Experts: surgeons who perform more than 20 robotic-assisted surgeries, minimally invasive procedures and non-invasive procedures each per month.
- Novices: surgeons who perform more than 20 minimally invasive procedures and non-invasive procedures each per month but no robotic-assisted surgeries.

As mentioned before, defining experts by the number of surgeries is not trivial and also depends on the speciality. However in this work, we selected our threshold of 20 surgeries based on works such as [50, 66]. With these criteria, we worked with 19 novices and nine experts. All the analyses of the remaining sections are taken from these two subgroups.

2.2 Visualizations Description

Information is essential to understand our environment and its correct visualization determines our level of interpretation. Particularly in human-machine interaction, visual displays offer the highest bandwidth channel since our visual system is capable of acquiring more information than all other senses. Therefore, having a good representation of the information is crucial for supporting rapid interpretation of what is happening in the environment and effective decision-making.

2.2.1 Data and Task Description. Participants viewed videos taken from an in-vivo porcine dataset from the Hamlyn Center Laparoscopic / Endoscopic Video Library [42]. The video sequence was composed of stereo-pair images of size 720x288 recorded during 450 sec, in which tissue deformation was repeatedly exhibited due to the tool-tissue interaction. The dataset was acquired doing palpation on the tissue, varying factors such as illumination and position and orientation of the tool, as well as varying the force of the palpation. Palpation is clinically relevant since it is used to identify tumors, cut tissues and avoid penetration in the tissue. These videos included four different kinds of force visualizations, described below. After watching these videos, participants filled out a questionnaire (see Table II).

As in any Robotic-assisted surgical system, *which inherently lose all patient-surgeon interaction forces*, participating surgeons were provided with this internal view of the surgical region of interest. But how to estimate how much force is applied?

2.2.2 Estimating the Interaction Forces. The conservation principles of continuum mechanics specify that any change in shape of an elastic object is directly proportional to the applied force. Using these principles, we estimated online the forces applied in the dataset based on the observable deformation.

Roughly speaking, in our previous work [2, 3] we proposed an energy functional based on L^2 in which the minimization of the residual error was changed by a maximum likelihood type estimator. Also, we guarantee the anatomy preservation by proposing a topology regularizer. Once deformation was computed, we used a learning system to find either the nonlinear relationship between deformation of different tissues and force, or a mixture elements model (by maximizing a likelihood function), to assign the value to a particular color label. This estimation was used as the force feedback information displayed to the users. Because the applied forces were estimated rather than directly measured, the feedback information likely did not exactly reflect the true forces, but our method provided a good approximation for current purposes. This approximation could be refined in future work by incorporating other means of modeling the applied force.

2.2.3 Visualizations Design. For displaying the force information as previously explained, we designed four different visualizations (described below) which are labeled based on the indicator used: Circle, Bar, Heat Map and Traffic light. Each of these visualizations has been used in past works. Our goal here was to compare surgeons' relative preferences for these relatively common visualization types and use their judgments to develop an evidence-based set of *best practices* for using visualizations to convey force feedback information in future work. Illustration of these visualizations can be seen in Fig. 3.

Circle This visualization provides force feedback information by means of a dynamic circle that tracks the tool tip. The circle fluctuates between four different color indicators corresponding to the magnitude of force. When no force is applied, there is no circle embedded in the environment. This representation has been used previously in [1, 56].

Bar The force is represented by a dynamic bar at the top-right corner of the display. The bar fluctuates between five states representing the intensity of applied force. In contrast with the previous visualization, this option presents stacked states, that is, past states remain displayed during the current state. This representation has been used previously in [30, 62].

Heat map A heat map is shown at the top-right corner of the view. In this visualization, force is denoted by the level of deformation that the tissue undergoes. The level of risk is represented by the color intensity where darker shades correspond to larger forces (risk). This representation has been used previously in [26].

Traffic light For this option, a traffic light type visualization is displayed at the top-right corner of the environment. It fluctuates between four color indicators illustrating the magnitude of the applied force. The traffic light also shows a void state (colorless) which indicates no force. This representation has been used previously in [21].

Table 1. Color-coding used at each visualization to indicate the level of risk depending on the force applied

Indicator	Coding-color	Meaning
Circle (System A) Bar (System B) Traffic light (System D)	Green	Risk-free – represents minimal interaction forces
	Yellow	Minimal Risk – symbolizes a safe amount of force
	Orange	Potential Risk – references a potential damage in the tissue
	Red	Risk – warning the physician of a tissue damage
Heat map (System C)	Yellow	No force – There are no interaction forces
	Red	Minimal Risk – represents a safe amount of force
	Black	Risk – denotes tissue damage

These visualizations were selected based not only on technical aspects, where we took into consideration the limited bounded domain of the display, but as well psychological ones, where we used typical color association and common cues like dynamic bars and traffic lights. The use of bar or circles is well-established in medical robotics experiments [1, 21, 30, 56, 62]. The selection of appropriate colors is important for adequate transfer of information. We followed a color-coding based on the perceptual phenomena related to colors. Based on the functional and sensory-social meaning of colors [25, 64], we used red for example to convey warning messages and green to indicate a small magnitude of force. Details of the color-coding we used in relation to the amount of applied force can be seen in Table 1. During the experimental procedure, we assigned letters to the visualizations as described in Table I. This assignment is the one used during the user study.

2.3 Experimental Procedure

After explaining the problem to the participating surgeons and giving the required instructions, they were provided with the four visualizations, those explained in subsection 2.2, each with a corresponding computer-based questionnaire. The instructions given were as follows: "We will display four different visualizations embedded in the robotic surgical system environment and labeled as System A, System B, System C and System D. Please interact with each visualization mode and respond to the corresponding questionnaire. At any time, you can return and interact again with any system and change any response in the questionnaire". The interaction was a passive one, in which users watched the prerecorded video demonstrating tool-use interaction, with one of the four visualization systems being overlaid on the video to convey information about the force applied in the video.

2.3.1 Visualizations Evaluation. Questionnaires are thought to be useful instruments to assess, for example, the usability and reliability of human-machine interfaces [52, 59]. For our study, we designed questionnaire items using a five-point Likert rating scale in which participants were asked to indicate the level of agreement with the given statements, ranging from Strongly disagree to Strongly agree. The questionnaire was composed of twenty-four questions, shown in Table 2, that *evaluated five human factors that are relevant in the context of human-machine interfaces.* These factors are not derived from the data (as might be the case in a Principal Components Analysis), but instead are common conceptual groupings of factors used in assessing usability and reliability in human-machine interfaces. These factors are thought to provide important insight into the perceptional flow of the end user [34, 37]. The factors are:

(1) Perceived Usefulness – Refers to the extent to which each participant believes that using each one of these systems will improve his/her surgical performance.

Table 2. Questionnaire used to evaluate each visualization option based on five human factor criteria

#	Statements	Human Factor Criteria
1.	Using the system during surgery would enable me to accomplish surgical tasks more quickly	Perceived Usefulness
2.	Using the system would improve the surgery performance	
3.	Using the system would enhance my effectiveness during the surgery	
4.	Using the system would make it easier to carry out the surgery	
5.	It gives me more control over the surgical task.	
6.	I would like to use this system during my surgeries	
7.	It is easy to understand the meaning of the visualization	Learnability
8.	It is easy to understand without instructions	
9.	It is easy to interpret the meaning of the color coding	
10.	I found it easy to adapt to the visualization	
11.	The system is designed for all levels of users	
12.	I quickly became skillful with the system	
13.	The visualization tool is distracting	Perceptual Limitation
14.	The visualization tool is logical	
15.	The visualization tool has a useful location	
16.	The provided colors are easily distinguished	
17.	I found the system unnecessarily complex	
18.	Is the assignment of color codes appropriate?	Consistency
19.	The display format is consistent	
20.	The display orientation is consistent	
21.	The data display is consistent with user conventions	
22.	Overall, I am satisfied with this system	Satisfaction
23.	Overall, the system is pleasant to use	
24.	Overall, the system works the way I want it to work	

All questions had a rating scale that went from Strongly disagree to Strongly agree. Moreover, two open-ended questions were asked: List the most negative aspect(s) and List the most positive aspect(s).

(2) Learnability – Denotes how easy it is to accomplish basic tasks and interpret outputs of a system.
(3) Perceptual Limitation – Indicates the degree to which participants respond to changes in each one of these systems using their sensory system.
(4) Consistency – The extent to which a participant agrees with the stimulus-response compatibility, that is, the input-output of the system exhibits a logical relationship.
(5) Satisfaction – Refers to the participants' level of comfort and acceptability of a given system.

The questionnaire contained two additional sections. The first was shown at the beginning of the session and acquired information about the expertise of the surgeon. The second was presented at the end of each questionnaire and was in the form of an open-ended question that asked surgeons to list the most positive and negative aspects of each visualization.

3 EXPERIMENTAL RESULTS

This section presents the analysis and results obtained from the data collected in the study. We have divided our evaluation into two main parts. The first is based on the use of statistical and graphical methods to extract participants preferences, while the second analyzes the results from the perceptual and cognitive point of view.

3.1 Evaluation Scheme

The aim of this study is to report findings and answer the questions presented in subsection 1.1. To achieve this, we used the following evaluation scheme:

First, we divided the collected data into two subgroups, experts and novices, to obtain the following:

- Analysis of the results based on the five different human factors: Fig. 4
- Non-parametric analysis of each human factor
- Overall analysis of data by subgroups (i.e. experts vs novices): Fig. 5

Secondly, we used the entire population of experts and novices combined to obtain the following:

- Evaluation of the combined results based on the five human factors: Fig. 6
- Overall analysis of data system by system: left side of Fig. 7
- Pairwise comparisons in the population data: right side of Fig. 7

Finally, we report an analysis based on different perceptual and cognitive principles.

- Evaluation of the principles based on attention, mental models, perception, and memory: Fig. 9

3.2 Analysis and Results

3.2.1 Statistical and Graphical Analysis. Prior to analysis, we assigned numerical values to the Likert scale response options, ranging from zero for *Strongly Disagree* to four for *Strongly Agree*. Next, we averaged each participant's numerical Likert scale responses across the questions associated with each human factor category. This yielded five average preference ratings for each participant one for each human factor. We then used the nonparametric Wilcoxon test to compare expert and novice ratings for each human factor, using the Benjamini-Yekutieli (BY) $p-$value adjustment to control for the false discovery rate. The results showed no statistically significant differences between experts and novices as defined in this study, for any of the human factors (all $p > 0.784$).

As Fig. 4-(a) shows, participants expressed the strongest preference for Systems A and D (70%) in terms of perceived usefulness. There was a clear rejection of System C by both groups.

The ease of completing tasks and interpreting outputs using each system were assessed by the learnability factor, the results of which are reported in Fig. 4-(b). Again, participants rated Systems A and D most highly on this factor. Similar to the previous factor, both groups showed a clear dislike for System C in terms of learnability.

The extent to which the users responded to the visual changes in a given system using their sensory modalities is illustrated in Fig. 4-(c). Although there were no significant differences between experts and novices for this factor, the plot shows a numerically higher preference for System D by experts (72%) while novices preferred System A (65%).

The logical consistency of each system is assessed in Fig. 4-(d). Both experts and novices indicated a strong preference of System A with a percentage greater than 75%. The plot also shows that experts reported System C as the one with the lowest consistency (50%) while novices reported System D (54%) as the one with lowest score, although the nonparametric statistical analysis suggests these differences are not reliable. Finally, the level of comfort and acceptability for each visualization can be seen in Fig. 4-(e). Again, there were no reliable differences between experts and novices for this human factor, but the plot indicates a numerical preference for System A by novices (77%). Both subgroups reported less satisfaction for System C.

For a better understanding and visualization of the results, we aggregated the "strongly agree" and "agree" responses from the original 5-point Likert scale into a "positive" category, and aggregated "strongly disagree" and "disagree" responses into a "negative" category. Fig 5 shows that experts and novices expressed a strong preference for System A. Moreover, looking at the blue bars, we found that both groups gave the most negative rating to System C.

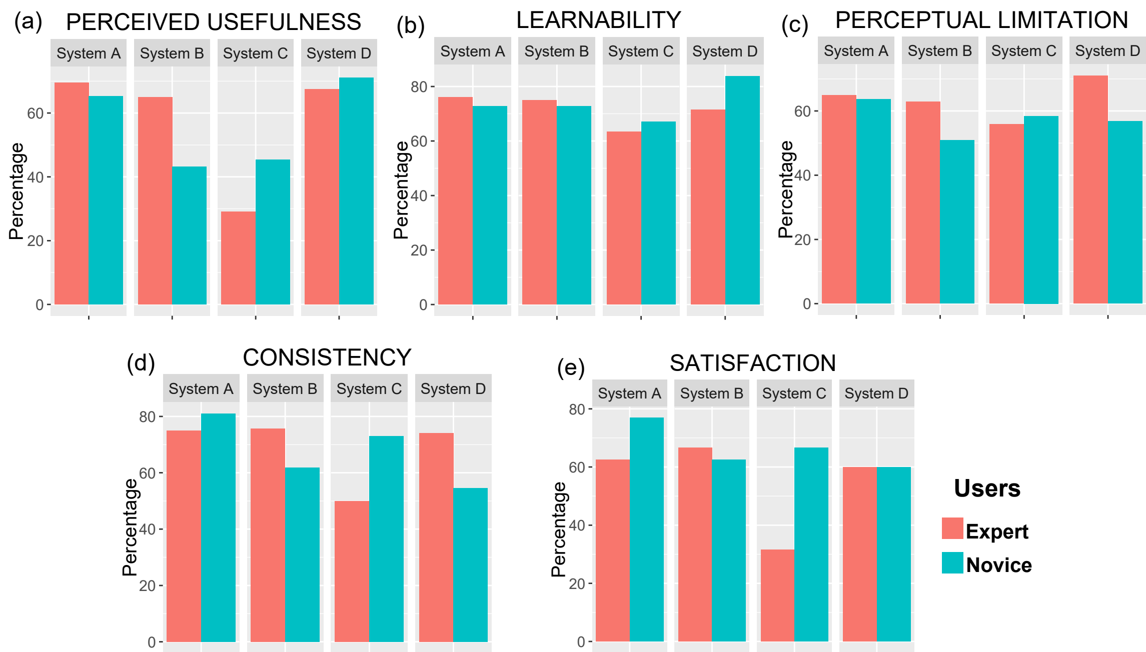

Fig. 4. Expert and Novices reference level per human factor. Each plot shows the percentage of acceptance of each system.

Because there were no reliable differences between experts and novices, we combined both subgroups and performed further analyses on the combined population. The results are shown graphically in Fig. 6 Numerically, System A was the best rated in three human factors: perceptual limitation, consistency and satisfaction. Although System D had the numerically highest preference scores for the perceived usefulness and learnability factors, the scores were only a few percentage points higher than for System A. Overall, System C was the worst rated with an average percentage across all factors of 52% while the most preferred were Systems A and D with an average of 71% and 66%.

We used the nonparametric Friedman test to statistically compare the four systems, collapsing over all the human factors. This test indicated a statistically significant difference between preference ratings across systems, $\chi^2(3) = 68.009$, $p < 0.001$ We then performed Nemenyi post-hoc tests with corrections for multiple comparisons. The results are shown in the right-side of Fig. 7 . These analyses showed that ratings for System C were significantly lower ($p < 0.05$) than for Systems A, B and D with p values < 0.001) in all cases. The other comparisons were not significant ($p > 0.05$).

Further analysis is shown at left-side Fig. 7 with an overview of the surgeons' preference after aggregating the data (as described earlier). The red bars show that surgeons reflected the strongest preference for System A while expressing a hard rejection of System C (blue bars). In comparison to System A, the surgeons' responses to System D indicated a reduced level of positive comments and an increased level of neutral responses.

Apart from all the results reported so far, one of the most important findings is related to the significance of having a visual force feedback compared to having no feedback at all. The plots at the left side of Fig. 8 show a visual illustration of the surgeon population used in this study classified based on their specialties and then based on their level of expertise. Out of the entire population, only 5% of the novices reported that they prefer not having a visual feedback as illustrated in the bar chart at the right side of Fig. 8. Nonetheless, the majority,

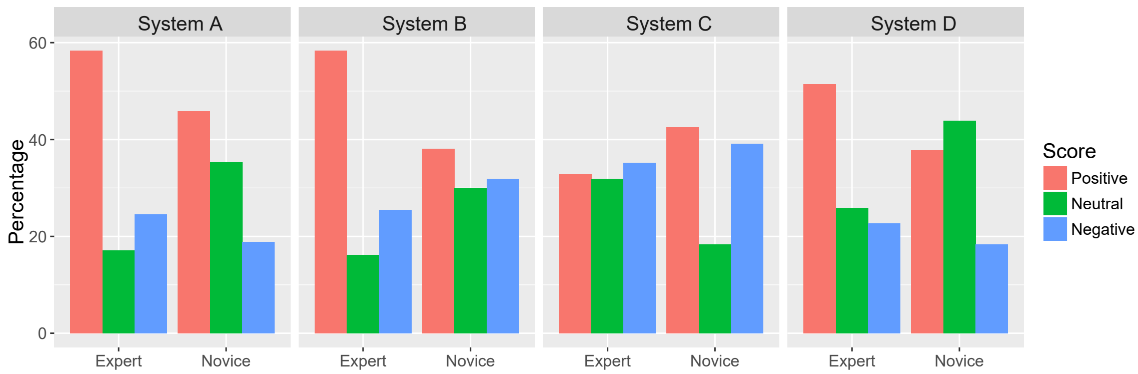

Fig. 5. Global view of the obtained results showing experts vs novices responses of each systems.

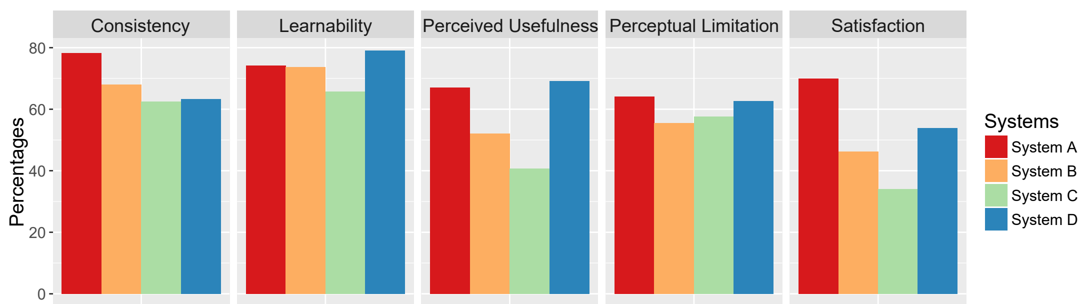

Fig. 6. Plots show the percentage of positive responses that each system received from the complete population per human factor.

composed of 100% of the experts and 95% of the novices, actually preferred the option of having a visual feedback of the force information. After viewing the different systems, they reported that the visual cues helped them to be more aware of the interactions taking place in the remote location and increased the level of transparency between them and the patient.

3.2.2 Perceptual and Cognitive Analysis. A primary goal of this experiment as a user study is to assess the user's subjective evaluation of the system. Users may or may not be able to provide reliable reports on their actual perceptual and cognitive processes while using the system, but as in other user studies, we assume that users' subjective reports are informative about aspects of the system they found helpful or problematic. System C was lowest. Systems A, B and D were statistically indistinguishable.

While past work has dealt with the lack of force feedback for RASS, most of these studies have not fully taken into account the *end user*. The challenge of developing new visualization techniques while keeping in mind the end user has been considered in different works such as [9, 14, 71]. In Fig. 9, we summarize the advantages and disadvantages of each visualization based on the surgeons' feedback.

Fig. 9 shows that Systems B, C and D present the force-feedback information at the top-right corner of the display. This placement requires users to make frequent eye movements back and forth between the visualized tissue and the feedback display. This likely places additional demands on perceptual and cognitive resources and

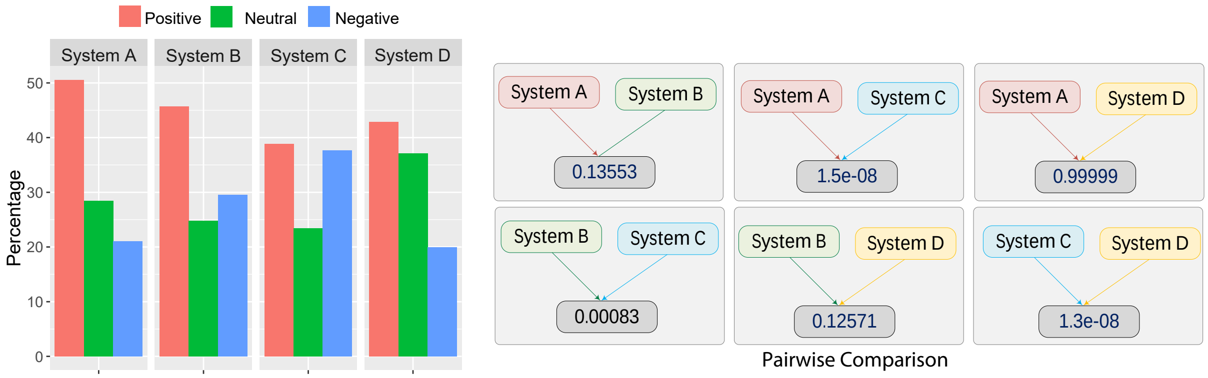

Fig. 7. (Left side) Total responses evaluating each system received from the whole population. (Right side) $p-$values obtained from a post-hoc test for multiple comparisons.

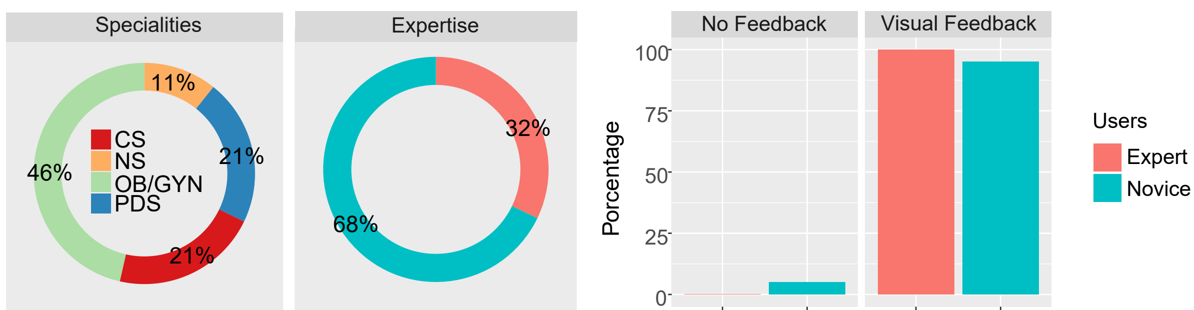

Fig. 8. (From left to right) Population in our experiments comes from four specialities which we divided into two clusters (experts and novices). Distribution of the preference of the users in which 95% of the novices and 100% of the experts preferred visual feedback.

could in turn impact both user performance and user preference with frequent use. System A minimizes this factor by placing the feedback display closer to the tissue of interest.

Our participants' responses suggested a linkage between the complexity of the visualization and its learnability, such that the system rated most complex (System C) was also rated lowest in learnability. By contrast, Systems A, B and D were rated as less complex and were correspondingly rated higher in acceptability.

Another advantage of Systems B and D is based on the perceptual principle called *redundancy gain* [19], which states that redundantly encoding information in more than one way can be beneficial for performance as it promotes faster learning and understanding. In the case of these two systems, information is coded using both color and position. Even though color is a fundamental component for visualization, around $\sim$ 10% of the world population has a color vision deficiency, which makes having redundant encoding, in this case position, advantageous for detecting and understanding. Further accommodations for users with color vision deficiencies can be implemented by providing alternative color-coding schemes that avoid frequently-confused colors. It is worth noting that System A could be augmented in future work to leverage redundancy gain by, for example, using a color-bar similar to that in System B and putting it instead on the tool.

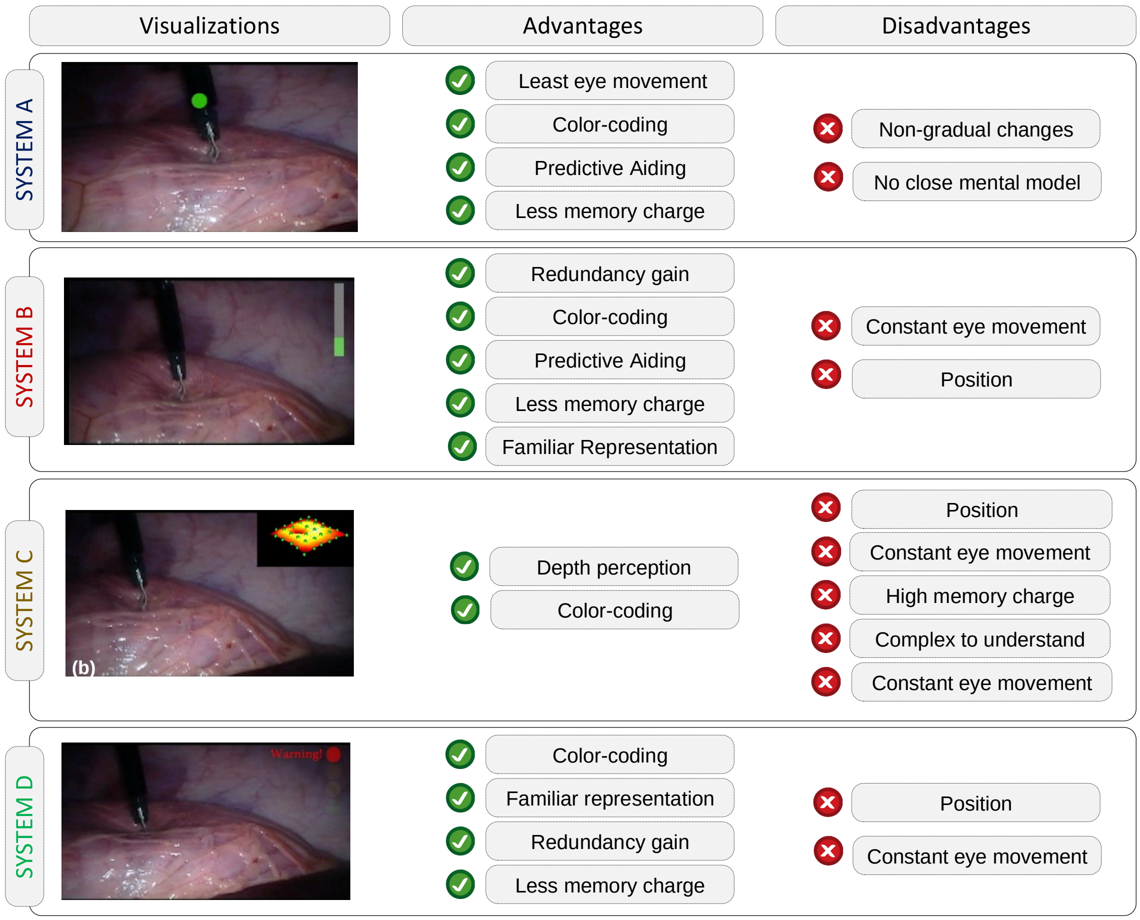

Fig. 9. The advantages and disadvantages of each visualization system as reported by the users.

Although surgeons agreed that all the visualizations displayed the information according to what is happening in the surgical environment, they rated System C relatively low in terms of consistency with user conventions. This suggests that the representation used in this system was relatively unfamiliar for the surgeons. This was likely related to the increased ratings of complexity and distraction for System C.

The limited capacity of working memory (or short-term memory) capacity is also important to consider when displaying information. Surgeons have a variety of factors to monitor simultaneously when they perform a robotic-assisted procedure, like controlling the pedals and fulcrum, and this makes it important to reduce working memory load wherever possible. Users reported that Systems A, B, and D were less demanding of memory and rated them relatively high in learnability.

Based on previous findings, we can summarize our recommendations for displaying information in robotic surgical systems as follows:

- Avoid overlapping information over the region of interest for the surgeon.
- Place the visual cue as close as possible to the surgical tool if it is of a small size (e.g. see Fig. 8 System A).

- If the visual cue is big, such as the visualizations shown in Fig. 8 System B and D, avoid placing it on the surgical tool. This is because it could cause distraction and might not fit on the tool at all times when the tool is partially visible (i.e. only part of the tool is in the current field of view).
- Use a color-coding that is compatible with the mental model of the surgeon. A simple but good example is using green-yellow-red. A relatively simple way to augment this recommendation to accommodate users having color vision deficiencies would be to provide the option of using an alterantive color-coding scheme that avoids using colors that are typically confused.
- Use a simple but efficient geometric shapes (for example see Fig. 8 Systems A, B and C).
- Do not overburden the display. You can include text but only in cases where it is needed, such as in a dangerous situation (e.g. see Fig. 8 Systems D).
- Offer visual cues that represent the information with more than one cue, such as position and color (e.g. see Fig. 8 Systems B and D).

4 CONCLUSION

The absence of force feedback in robotic surgical systems continues to be one its major limitations and is one of the reasons why surgeons need to go through extensive training to accommodate the indirect interaction. Having interaction forces information is of huge importance since it is directly related to the reduction of complexity of the surgical task in hand. This information has also been shown to increase the transparency between the operating surgeon and the patient as it gives the sensation of direct interaction. Although the current literature in medical robotics is quite large, the topic of designing a proper visual display of force feedback has not yet been sufficiently discussed. This is a very important aspect since having an effective visualization of force information has direct repercussions on the surgeons' performance, particularly when it takes into account the perceptual and cognitive principles that are relevant for the surgeon.

The main goal of this work was twofold. First, to carefully assess the use of visual cues to transmit information about interaction forces information, and second, to offer recommendations for proper design of visual displays based on the surgeons' preference. To achieve these two goals, we conducted a clinical study to demonstrate the potential benefits of using visual feedback taking into account the opinion and preference of the end users, i.e. the operating surgeons. Out of the entire population, 96% of participating surgeons preferred having the visual feedback over none. Going back to the questions we posed in subsection 1.1, we found that in order to present the force information in a way that can be easily interpreted, we have to take into account the surgeon's mental model. That is, the visual cues used to convey the force information should mesh well with the perceptional and cognitive abilities of the end user.

In this work, we conducted an initial study focusing on the perception of the operating surgeons. Future work will include a more extensive evaluation to test the clinical potential of our findings. This future work will be based on a long-term follow-up study with the aim of evaluating a variety of other factors, such as: learning curves of performing surgery with visual feedback, adaptability time, the impact of visual feedback in terms of improving surgery procedures, and safety. A parallel study will be performed, involving combinations of the vibrotactile and auditory modalities with other sensory modalities. Taken together, the aim of these future studies is to provide an evidence-based foundation for evaluating the potentials and advantages of using visual feedback in clinical practice.

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