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Review – Education

Rethinking Autonomous Surgery: Focusing on Enhancement over Autonomy

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Abstract

Context: As robot-assisted surgery is increasingly used in surgical care, the engineering research effort towards surgical automation has also increased significantly. Automation promises to enhance surgical outcomes, offload mundane or repetitive tasks, and improve workflow. However, we must ask an important question: should autonomous surgery be our long-term goal?
Objective: To provide an overview of the engineering requirements for automating control systems, summarize technical challenges in automated robotic surgery, and review sensing and modeling techniques to capture real-time human behaviors for integration into the robotic control loop for enhanced shared or collaborative control.
Evidence acquisition: We performed a nonsystematic search of the English language literature up to March 25, 2021. We included original studies related to automation in robot-assisted laparoscopic surgery and human-centered sensing and modeling.
Evidence synthesis: We identified four comprehensive review papers that present techniques for automating portions of surgical tasks. Sixteen studies relate to human-centered sensing technologies and 23 to computer vision and/or advanced artificial intelligence or machine learning methods for skill assessment. Twenty-two studies evaluate or review the role of haptic or adaptive guidance during some learning task, with only a few applied to robotic surgery. Finally, only three studies discuss the role of some form of training in patient outcomes and none evaluated the effects of full or semi-autonomy on patient outcomes.
Conclusions: Rather than focusing on autonomy, which eliminates the surgeon from the loop, research centered on more fully understanding the surgeon's behaviors, goals, and limitations could facilitate a superior class of collaborative surgical robots that could be more effective and intelligent than automation alone.
Patient summary: We reviewed the literature for studies on automation in surgical robotics and on modeling of human behavior in human-machine interaction. The main application is to enhance the ability of surgical robotic systems to collaborate more effectively and intelligently with human surgeon operators.

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1. Introduction

Since the word “robot” was first popularized in a Czech science fiction play in 1921, we have seen incredible advances in the technology and applications of robotics and automation. Robot-assisted surgery is particularly beneficial in urology, where surgical dexterity is paramount for complex procedures. For example, robotic assistance can lead to fewer complications in cystectomy [1], along with other potential benefits [2]. It has also been shown that prostatectomy and nephrectomy benefit from robotic assistance [3,4].

However, commercially available surgical robots have fallen short of the ultimate vision of a robotic system that is capable of sensing its environment and performing actions (either simple or complex) in a fully autonomous manner. As the technology continues to improve, it is natural to wonder if surgical robots will one day be fully autonomous, eliminating the need for a surgeon.

In the surgical world, any surgery performed with a robot is termed robot-assisted surgery (RAS). Rather than aim for the goal of full autonomy, which may be misguided and currently not possible, we envision a more realistic and beneficial model to push forward the level of assistance offered by the robot, bringing it to the level of robot-enhanced surgery (RES).

In this review, we first provide a short tutorial on the challenges of fully automating a system from an engineering controls perspective. We give a brief overview of the current state of surgical robotics research as it relates to various levels of autonomy. We also summarize technologies and techniques to enhance the intelligence of the robotic system as it relates to understanding the surgeon operator. We hope to convey that the design of more collaborative and adaptive robot partners that leverage surgeon strengths and help to overcome limitations might be a more feasible and effective near-term goal.

2. Evidence acquisition

We performed a nonsystematic search of the English language literature using Google Scholar, Scopus, and the PubMed-MEDLINE database up to March 25, 2021. Keyword and title searches were conducted for topics related to robotic surgery, ranging from general searches such as “autonomous robotic surgery” to more specific terms such as “force measurements in robotic surgery”, “surgical skill assessment”, “physiological sensing”, and “computer vision for robotic surgery”. We included original studies related to automation in RAS and human-centered sensing and modeling, as well as previous reviews on relevant topics.

3. Evidence synthesis

Table 1 summarizes the studies identified in the nonsystematic search [5–56].

3.1. *Towards autonomous surgery: what do we need?*

In robotic control theory, the behavior of a robot is controlled using a theoretical framework that is applied to the physical world through a variety of sensors and actuators. While a rigorous description of automated control is beyond the scope of this paper, we introduce some basic requirements for truly autonomous surgical robots. Figure 1 shows how robotic surgery can be described as a closed-loop control problem, with three major elements: a model of expertise, physical reality, and measured reality, the approximate representation of the real world.

The *model of expertise* represents the intelligence of the robotic system. It contains a mathematical model of the desired outcome (e.g., a surgical outcome) that is used to generate a control action for the physical robot. The *physical reality* block is composed of all the physical actors involved in RAS: the patient, the surgeon, and the robotic hardware. Finally, the *measured reality* block is a representation of how the robot can see and understand the physical reality through sensor measurements. The goal of all modern control systems is to find the error between the measured reality and model of expertise in order to generate meaningful and effective feedback to push the physical reality closer to ideal behavior and minimize errors. The frequency of this control loop must be fast enough for meaningful and stable control (Fig. 2). For all control systems, it is essential that each element of the control feedback loop is fully defined in a mathematically rigorous way to ensure the safety and effectiveness of the overall system.

3.2. *Levels of autonomy in robotic surgery*

One of the great strengths of robotic control systems is that the level or degree of autonomy for a given system can be a design choice, and one that is not necessarily a binary choice. Borrowing from classifications developed for self-driving cars, Yang et al [57] classified autonomy for medical robots on a scale from 0 to 5, with 0 corresponding to no autonomy, with the surgeon remaining in full control, and 5 to a system fully capable of performing entire surgeries, with no human input (Fig. 3). Two recent reviews used similar classification methods for surgical robot autonomy, reviewing both academic research results and commercially available surgical robotic platforms [58,59]. Yip and Das [58] provide an overview of commercially available or otherwise well-known surgical robots, while Attanasio et al [59] provide a comprehensive review summarizing the current state of automating specific types of surgical procedures (eg, knot tying, supervised suturing, organ and tumor segmentation, ablation) across a variety of surgical specialties from urology to orthopedics. The majority of surgical robotic systems that are either in, or nearing, clinical use, fall at either end of the autonomy spectrum rather than the middle. Arguably, design at the ends of the spectrum represents an easier technological challenge: the engineering problem either simplifies to eliminating any intelligence in the robotic system (such as the da Vinci Surgical System; Intuitive Surgical, Sunnyvale, CA, USA) or fully eliminating the most unpredictable and dynamic element of the control loop, the human operator (eg, ROBODOC [CUREXO, Fremont, CA, USA] for supervised autonomous orthopedic surgery and

Table 1 – Topics and references identified in the literature review

Topic	Article type and references	Evaluation type (when present)	Open issues
Model of expertise			
Expertise metrics	Research [5–8]	Nonrandomized controlled trial [5–8]	No ground truth for surgical expertise
Data-driven modeling	Nonsystematic review [9] Research [10–14]	Technical validation [10–14]	Sparse data available for model training, black-box algorithms do not easily translate to training strategies
Measured reality			
Physiological	Nonsystematic review [15–17] Research [18–21]	Validation of measurements [18,20,21] Crossover trial [19]	Baseline data collections and wearable sensors are always required
Vision-based	Nonsystematic review [22–25] Systematic review [26] Research [27–31]	Technical validation [27–31]	Persisting challenges in image segmentation, black-box algorithms do not easily translate to training strategies
Motion-based	Nonsystematic review [32] Research [33–36]	Validation of measurements [33] Validation of assessment [34–36]	Augmenting robot sensing capabilities
Physical reality			
Reflective haptic feedback	Nonsystematic review Systematic review [38] Research [39–43]	Randomized crossover trial [42] Crossover trial [39–41,43]	Existing methods lack realism, methods to enhance fidelity not feasible for real-time human interaction owing to computational complexity
Haptic movement guidance	Research [44–52]	Demonstration only [44] Crossover trial [45,50,51] Randomized concurrent controlled trial [46,52] Psychophysics (accuracy) [47,48] Randomized crossover trial [49]	Paucity of guidelines on effective feedback strategies, variability across human learners
Adaptive training guidance	Nonsystematic review [53], Tutorial [54], Opinion [55], Research [56]	Randomized concurrent controlled trial [56]	Paucity in the literature, lack of methods for unstructured (ie, not predefined) movement tasks

CyberKnife [Accuracy, Sunnyvale, CA, USA] for radiological treatments [58]).

Another important technical distinction is that automatic behavior, whereby the robot executes rigid predetermined behavior, is very different from autonomous behavior, whereby the robot is able to modify its behavior in real time and change its planning to react to unexpected events [59]. This ability to deal with the unexpected is the ultimate benchmark to compare the performance of a human with that of a robot. While artificial intelligence (AI) is developing rapidly and has shown applications in improving diagnostic capabilities [60], the technology still lacks the level of sophistication required for true autonomy, and this remains a major technical challenge in the design of all robotic systems, not just those designed for surgery.

Finally, beyond technical challenges, there are significant regulatory, legal, and ethical concerns associated with the deployment of autonomous surgical robots [57]. When errors and patient harm occur, who bears the legal responsibility for autonomous surgical robots, the surgeon, the hospital, the robot, or the engineer who designed the robot [61]?

With these considerations in mind, it is clear that keeping a human in the surgical robot control loop is critical, at least in the near term. However, to allow natural and seamless collaboration between humans and robots, the robotic system needs more information about the surgeon's intent and ability to carry out the intended task. In the next sections, we review the different aspects necessary for the control framework for semi-autonomous, collaborative, surgical robots and highlight technologies and techniques to better model surgeon behavior and skill levels in ways that can be integrated into the real-time robot control loop.

3.3. *Measured reality: using sensors to quantify surgical expertise*

In this section we review the technology available for quantitative measurement of the surgeon, robot, and patient environment (Fig. 4 [62–65]). Broadly speaking, sensing for RAS can be divided in three categories: motion-related measurements, which capture information on the movement of the actors involved and the forces that they exchange; physiological sensing, which records physiological information from the human in the loop; and vision-based sensing, which provides the robot with a more generalized and high-level understanding of the environment, often involving advanced processing techniques such as machine learning. As robotic control systems tend to operate between 100 and 1000 Hz, it is important that sensors used to measure the real world can be sampled at similar speeds.

3.3.1. *Motion-related sensing*

Robots sense and take commands using simple variables, such as position and velocity, to accomplish tasks. While turning these measurements into metrics that can define a model of good surgery is challenging, obtaining the measurements themselves is relatively straightforward. For example, force sensors can be embedded in surgical tools [33] and kinematic sensors can be embedded into the joints of the robotic systems [32]. Measurements on the human surgeon can also be useful for human-robot collaboration and for the development of better models of surgical expertise. In this case, kinematic measurements can be obtained, for example, via wireless sensors [34], electromagnetic sensors [35], and optical and camera trackers [36].

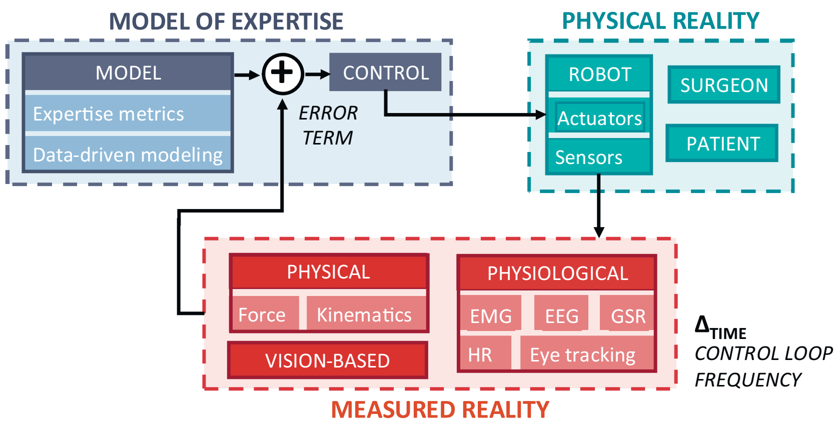


Fig. 1 – Closed-loop control for automated surgery. Control begins with a model of a desired behavior, such as surgical expertise. The physical surgeon-robot behavior is then measured using sensors and compared to the original model of expertise. Errors are used to provide some form of feedback to the surgeon or robot to enhance performance in near real time.

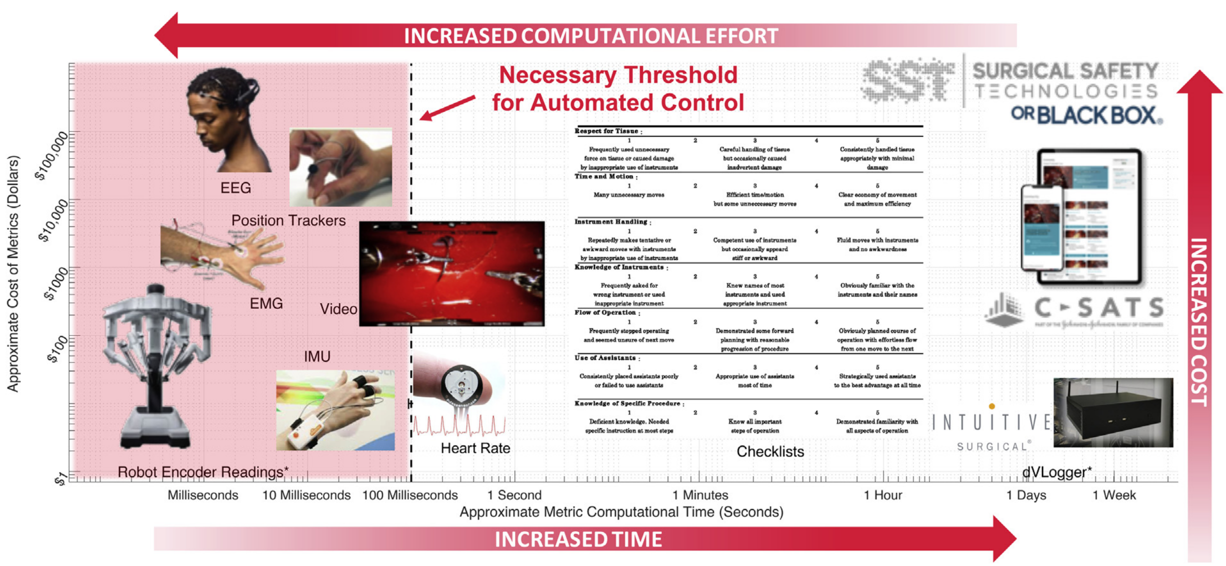


Fig. 2 – Overview of the technology available for measurements in robotic surgery. Automated surgery or intelligent feedback to the surgeon requires sensors that provide measurement data fast enough for computer control. EEG = electroencephalography; EMG = electromyography; IMU = inertial measurement units.

3.3.2. *Physiological sensing*

Physiological measurements obtained from human surgeons have been linked to expertise level, workload, stress, and other factors. For example, eye motions can be used to classify surgical expertise levels [18]. The number of eye blinks serves as an indicator of stress and concentration levels during training [19], while galvanic skin response (changes in skin electrical conductance) can be used to estimate cognitive load, attention, and emotional state [20]. Surface electromyography measures the electrical signals from active muscles, which can reveal the underlying motor patterns, physical effort, and motion intent [15,16]. It has been shown that heart rate and its variability capture the dynamic workload, emotion, and cumulative stress [17]. Finally, electroencephalography can quantify human emotion, perception, cognition, and technical skills [21]. These sensing technologies are promising in that they take direct measurements from the human operator; however, wearable sensing can be cumbersome and the interpretation of these data can be challenging.

3.3.3. *Vision-based sensing*

The field of computer vision (CV) aims to transform visual input stimuli into meaningful mathematical representations that can be manipulated by algorithms downstream to execute various higher-level tasks, such as object detection. Analogous to the human visual system, CV-based sensing for robot-oriented surgical analysis can provide a tremendous amount of information moment-to-moment to guide the formation and refinement of dynamic models of the operating theater (Fig. 5 [27–29,66]). Although the ultimate goal of visually "perceiving" real-time surgeries at the level of an expert

Fig. 3 – Levels of autonomy possible in robotic surgery range from no autonomy, with the surgeon in full control, to full automation, with no human input. Copyright© 2017, American Association for the Advancement of Science. Reproduced with permission from Tang et al [57].

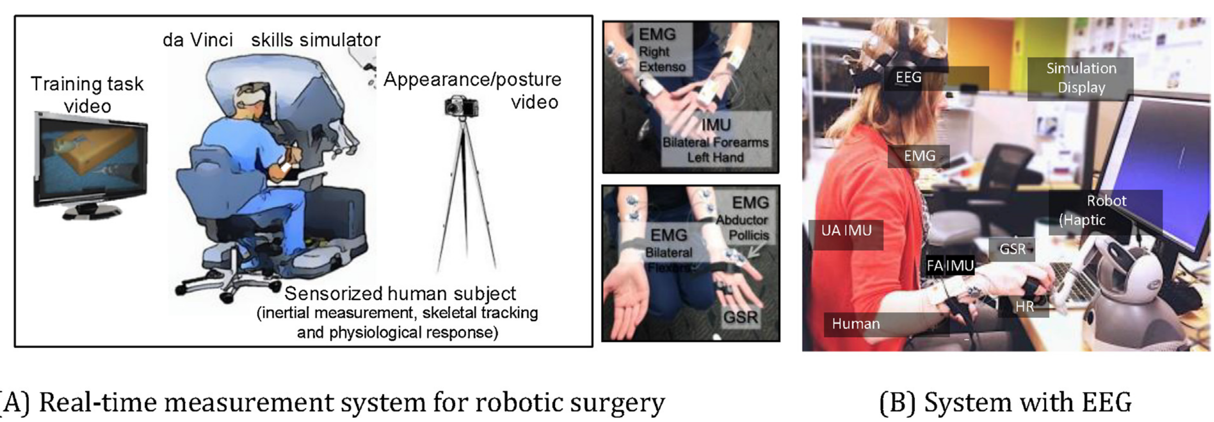
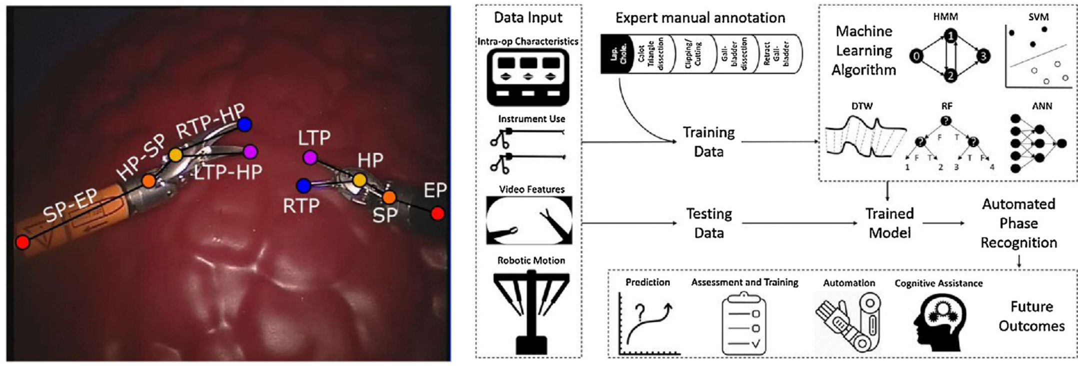


Fig. 4 – Examples of real-time measurement systems for modeling of human behavior in robotic surgery [62–64] and human-computer interaction [65], including video data, human-centric EMG, EEG, and GSR measurements, inertial measurement, and position tracking. EEG = electroencephalography; EMG = electromyography; FA = forearm; GSR = galvanic skin response; HR = heart rate; IMU = inertial measurement units; UA = upper arm.

surgeon (or superior) remains distant, significant technical progress continues to be made, piecewise, in allowing quantitative, vision-based feedback for guiding and informing robotic surgery. Video-based methods have been proposed for a variety of relevant objectives [22], including characterization of tool articulation and kinematics [27,28], phase and step recognition in surgical procedures [29], classification of action, gestures, and tasks [26], and assessment of surgical skill [23,30,31]. Notably, at the heart of state-of-the-art approaches to surgical video analysis is deep learning (DL), a subfield of machine learning involving models that can automatically learn multiple layers of data representation to capture increasingly complex patterns in a hierarchical fashion [24]. Progress in DL research has been the most important technological development in recent years for advancing CV and AI in general [25].



(A) Vision-based instrument detection [27] © 2020 IEEE (B) Video-based surgical phase recognition [66]

Fig. 5 – Examples of surgical video analysis techniques, including detection and characterization of the articulation and movement of the surgical instrument [27,28] and surgical phase recognition [29,66]. LTP = left tip point; RTP = right tip point; HP = head point; SP = shaft point; EP = end point; HMM = hidden Markov model; SVM = support vector machine; DTW = dynamic time warping; RF = random forest; ANN = artificial neural network.

3.4. Modeling expertise: defining surgical mastery quantitatively

A second key aspect of a collaborative control framework is the internal model of expertise that gives the robotic system a reference or ideal trajectory for good surgical behavior. This includes both a quantitative understanding of what surgical expertise is and the formulation of a concrete plan to perform the necessary tasks. Combined, these steps represent the control action that will be executed by the robotic system to achieve ideal performance.

3.4.1. Kinematic modeling of expertise

As discussed in the previous sections, modern techniques for motion tracking facilitate data collection and analysis during surgical procedures that can be used to quantitatively define good performance for robotic systems. In the research community, the fundamental movements of surgery, referred to as *bases* of movement, can define the underlying structure and building blocks of surgical movement. Bases of surgical movements have primarily been created by learning from demonstration [9], in which machine learning techniques are used to teach a robot how to move on the basis of data collected from humans. Characterizing surgical movements can aid in the assessment of surgical skills such as expertise level [5] or surgical style [11]. For instance, a statistical analysis of jerk, typically related to the smoothness or crispness of a movement, can distinguish experts from novices [6]. More complex analysis can be performed with larger data sets by implementing machine learning techniques to assess surgical skill [14,67].

3.4.2. Post-completion task-level metrics of expertise

Another way to quantify surgical expertise is through task-level metrics such as completion time, path length, economy of volume, and mistakes made during execution. These types of metric are often used to evaluate the surgical training outcomes and their construct validity, and the ability to identify high levels of expertise has been extensively studied in the literature [7,8]. In addition to providing post-training evaluation, post-task metrics can also be used to provide benchmarks for surgical proficiency or as a measure of optimization by a robotic control system.

3.4.3. Real-time metrics of expertise

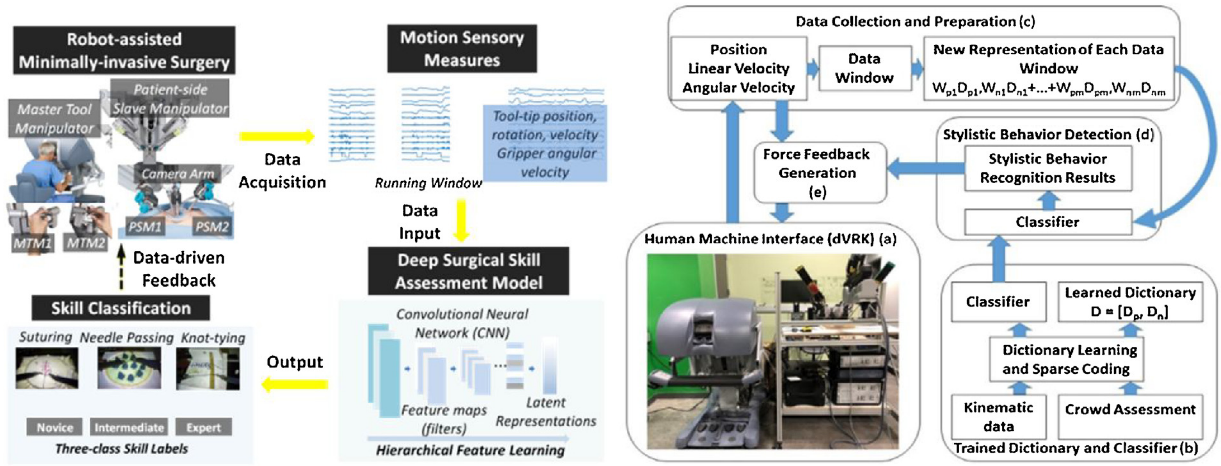
While post-completion task evaluation is useful for quantifying proficiency, it cannot be used to evaluate skill during a procedure. Real-time evaluation is necessary for any level of robotic automation. Real-time evaluation of expertise is challenging and is still an open research topic. Some recent techniques compare tool trajectories to “optimal” trajectories [12] or use streamed kinematic data to classify stylistic behavior [13]. Other work has been done to facilitate extraction of the most relevant information during surgery for expertise evaluation, thus reducing the memory and computational effort needed [10]. While these results are promising, advances in the field are still not at a stage at which such information can be integrated in a completely automated robotic loop.

3.4.4. Control actions

Assuming that the robot has a correct representation of good surgery, the control actions represent the planned steps necessary to achieve good surgery. This is a challenging aspect of robotic surgery and the one that, together with real-time evaluation of expertise, represents the greatest barrier to automated and semi-automated surgery. Indeed, while it is possible to automate some specific tasks within a surgical procedure [68], to the best of our knowledge there are no fully automated surgical robots.

3.4.5. Physical reality: evaluation of feedback effectiveness

The final step towards designing effective and collaborative intelligent surgical robots is to ensure that the feedback provided to the surgeon is intuitive, natural, and effective (Fig. 6). Because of the uniqueness and complexity of the human perceptual system, the design of universally effective feedback is a major technical challenge.



(A) Near–real-time skill classification [67] (B) Near–real-time stylistic feedback

Fig. 6 – Examples of near–real-time surgical skill prediction and feedback systems, including (A) a framework capable of classifying surgical expertise from kinematic data in a 1–2-s sliding window, reproduced from [67], and (B) a stylistic detection method that computes stylistic deficiencies every 0.25 s [13]. MTM = master tool manipulator; PSM = patient-side manipulator; dVRK = da Vinci research kit.

Many surgical robot prototypes and surgical robotic simulators have been used to evaluate the effects of adding reflective haptic feedback (eg, providing users with a force model of the surgical environment) and revealed improvements in performance [37,39–41]. Force feedback can also improve the development of psychomotor skills for early surgical trainees [38,42]. However, reflective force feedback lacks the fidelity needed to accurately represent the surgical environment and is often perceived negatively by the user [43].

An alternative approach to reflective haptic feedback is guidance haptic feedback, in which the goal is not to simulate the patient's tissue properties but rather to enhance motor learning via haptic or tactile motion cues—cues that become critical in human-robot collaborative environments. Studies have shown the effectiveness of haptic feedback in developing motor skills [44–46] and guiding movement [47–49]. A common type of training of motor skills with haptic feedback involves recording an expert's movements and having a novice follow those movements, with haptic feedback provided if they deviate from the intended path [50]. However, if the feedback gains are too strong, learning can be negatively impacted [51]. By contrast, haptic guidance designed to be less restrictive and exploratory can allow the user to discover new movement strategies [52].

One opportunity for guidance haptic feedback is in the domain of adaptive training. Adaptive training is typically used in video gaming, rehabilitation, medical simulation, and industrial training as a way to optimize learning by providing trainee-specific content [53]. Typically, some adaptive variable (eg, performance) is measured in real time and used to adapt the learning environment in real time (eg, increase the task difficulty) [54,55]. The first adaptive training study for a surgical robot, published in 2018, used haptic assistance–as-needed to keep a ring centered during a rail-following task. The results showed faster learning curves for eight novices with assistance when compared to eight novices without assistance, although the difference was not statistically significant [56]. The haptic assistance in this study was directly related to the task (eg, computed from position differences between the ring and rail) and only one haptic gain was evaluated. Despite these limitations, this study paves the way for personalized and adaptive feedback in surgical robotics.

Finally, the ultimate evaluation of any surgical feedback technique is the impact on patient outcomes. In general, there is a paucity of studies that relate patient outcomes to surgical training techniques [69], with limited work demonstrating some improvements to patient outcomes with simulation-based training [70,71]; however, to the best of our knowledge, there are no papers on the effects of autonomy levels or guidance cues on patient outcomes. These studies will be critical for future clinical adoption of semi- or fully autonomous surgical robots.

4. Conclusions

To allow full autonomy, it is critical to define the ideal behavior of a system, measure how well the physical system follows that behavior, and provide meaningful and effective feedback to the system to minimize any errors in near real time. For surgical robotics, there is a dearth of literature on all these aspects of autonomous control, making the road to full autonomous surgery a significant engineering challenge. However, if robotic systems could instead be designed to better understand and leverage the intelligence of the surgeon operator, they could be more effective and natural collaborators in the delivery of surgical care, paving the path from robot-assisted surgery towards true robot-enhanced surgery. Solving open challenges in surgeon-robot interaction such as predicting surgeon intent, measuring expertise levels, and determining competency during task execution, while providing effective and natural guidance to the surgeon operator, could help to accelerate the clinical adoption of more intelligent and collaborative surgical robots.

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Study concept and design: All authors.
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