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REVIEW ARTICLE

Surgical robotics beyond enhanced dexterity instrumentation: a survey of machine learning techniques and their role in intelligent and autonomous surgical actions

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Abstract

Purpose Advances in technology and computing play an increasingly important role in the evolution of modern surgical techniques and paradigms. This article reviews the current role of machine learning (ML) techniques in the context of surgery with a focus on surgical robotics (SR). Also, we provide a perspective on the future possibilities for enhancing the effectiveness of procedures by integrating ML in the operating room.

Methods The review is focused on ML techniques directly applied to surgery, surgical robotics, surgical training and assessment. The widespread use of ML methods in diagnosis and medical image computing is beyond the scope of the review. Searches were performed on PubMed and IEEE Explore using combinations of keywords: ML, surgery, robotics, surgical and medical robotics, skill learning, skill analysis and learning to perceive.

Results Studies making use of ML methods in the context of surgery are increasingly being reported. In particular, there is an increasing interest in using ML for developing tools to understand and model surgical skill and competence or to extract surgical workflow. Many researchers begin to integrate this understanding into the control of recent surgical robots and devices.

Conclusion ML is an expanding field. It is popular as it allows efficient processing of vast amounts of data for interpreting and real-time decision making. Already widely used in imaging and diagnosis, it is believed that ML will also play an important role in surgery and interventional treatments. In particular, ML could become a game changer into the conception of *cognitive surgical robots*. Such robots endowed with cognitive skills would assist the surgical team also on a cognitive level, such as possibly lowering the mental load of the team. For example, ML could help extracting surgical skill, learned through demonstration by human experts, and could transfer this to robotic skills. Such intelligent surgical assistance would significantly surpass the state of the art in surgical robotics. Current devices possess no intelligence whatsoever and are merely advanced and expensive instruments.

Keywords Surgical robotics · Skill learning · Skill analysis · Learning to perceive

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Motivation for machine learning in surgical robotics

To justify the cost of robotic surgery, technology providers and its users are searching for objective and measurable proof that robotic surgery possesses clinical advantages over existing manual techniques [1–3]. While such evidence remains sparse [4,5] or even discouraging at present [6–8], future systems that possess a certain degree of intelligence might show the clinical advantage people are looking for. Endowed with cognitive capabilities, surgical robots could take over the simpler parts of a task and allow surgeons to focus on the more crucial and complex parts of the procedure. This could translate into increased reliability, performance or efficiency of robot-assisted interventions compared to more traditional ones. Indeed, some of the selling arguments of ML techniques are exactly that they allow *smoother trajectories*, more *accurate* or *faster* execution of repetitive and time-consuming tasks [9]. Through synthesis of technical or cognitive knowledge coming from a broad group of expert surgeons, the system could acquire and possibly display similar expertise during the intervention. Such system could play the role of a highly-skilled 'computerized assistant' that provides the right technical assistance at the right instant of time, during routine or even unusual interventions [2]. This could translate toward increased reliability or improved outcome of robot-assisted interventions compared to traditional interventions.

The aging population, a reduced workforce and an increasing workload on expert surgeons are further incentives to introduce computerized assistants or even automate certain surgical interventions. This idea is not new. Automation has been investigated since the early days of SR, for instance, systems like the Unimation Puma 200 from Kwoh et al. [10], the ROBODOC [11], MINERVA [12] or Cyberknife [13] operated largely automatically. All these systems work in an environment that shows a relatively large invariance with respect to the actual robotic action. However, such an assumption severely limits the range of procedures that can be considered or also the performance that can be achieved. Indeed, the majority of surgical interventions do interact with an effect on the environment, especially when interactions with soft, deformable structures are involved. Such interaction is the motivation behind the development of *visual servoing* techniques, namely to account for deformation and physiological motion. Typically, visual servoing techniques only focus on a specific detailed part of the surgical procedure. Visual servoing techniques aiming for accurate control of forces or interactions become difficult if based on visual information only. Substantial efforts have been done to *explicitly model* the interactions or tissue deformation. Excellent works have appeared that model trajectories and interactions during surgical tasks, e.g., for knot-tying [14], suturing [15], stitching [16], tissue retraction [17,18], puncturing [19], cochleostomy [20], anesthesia [21] or even diagnosis [22]. It should be noted that depending on particular choices of models and parameters, the predictive power or applicability of such models can be rather limited. Furthermore, the derivation of valid models and the identification of its parameters can be a time-consuming and tedious task. Given the large variability between people, organs and tissues, *explicit* modeling approaches have practical limitations.

In contrast, ML approaches that learn *implicit models* directly from real sensory data are appealing for the following reasons:

- general applicability to a wide range of problems and sub-tasks;
- avoidance of complex modeling of the underlying physics and biomechanics;
- based on real observations and data from case-based scenarios.

These properties explain why ML approaches have recently received more attention within the research community. Even for critical applications such as in surgery, they are increasingly being considered.

Introduction to machine learning

ML is a multidisciplinary field that provides computers with the ability to learn without being explicitly programmed to perform specific tasks [23,24]. While ML techniques have been used extensively in a wide spectrum of robotic applications, it is only recently that ML methods have been considered for SR. Currently, there is no general consensus on the definition of a robot. A robot in the context of this paper is a system that can perceive its environment through its sensors and generates actions using its end effectors to accomplish a variety of tasks. According to this definition, a robot is a physical system that has three components: sensors, actuators (end effectors) and a control architecture that processes sensory data and generates actions. Figure 1 shows a schematic of an ML-enabled intelligent surgical robotic system for the case of catheter-based interventions. The continuous interaction that takes place between the robot, the surgeon (domain expert) and the environment (human body) is an important feature of this scheme. The robot perceives the state of the environment through its sensors and executes an action based on this information. The environment determines the next robot state also based on the action that was executed by the robot. An action taken by the robot has an associated cost. The purpose is to learn a mapping function from perception $\boldsymbol{z}$ to action $\boldsymbol{a}$ that minimizes the total cost incurred. In SR, the mapping function from perception to action can be considered as the *surgical skill*. Such skill can be decomposed into two main parts. The first part is the state estimation. It maps the perception $\boldsymbol{z}$ to the estimated environment state $\hat{\boldsymbol{s}}$. The second part maps the estimated state $\hat{\boldsymbol{s}}$ to the action $\boldsymbol{a}$ to be taken. The cost quantifies the skill demonstrated by the robot or by the surgeon. It depends on the state $\boldsymbol{s}$ and the robot action $\boldsymbol{a}$.

The process of evaluating the learned skills is referred to as skill analysis. In this paper, a review of work in SR on

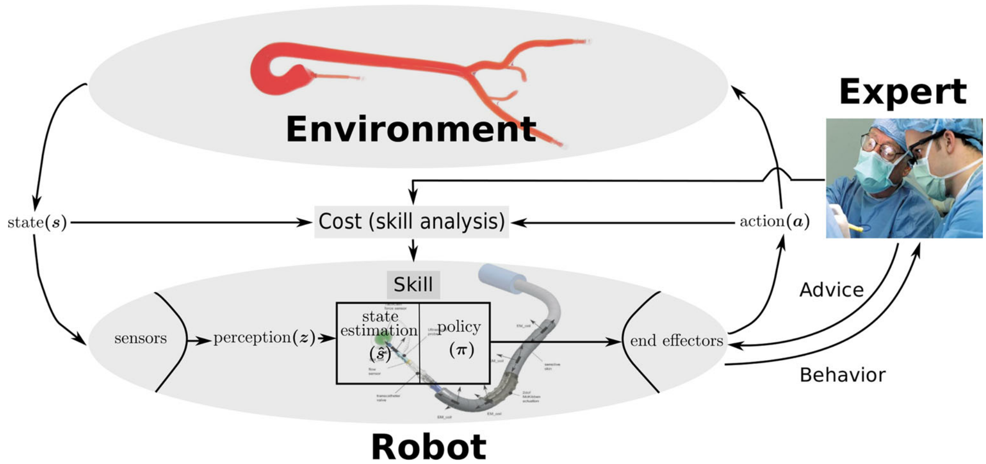

Fig. 1 Overview of a learning system in surgical robotics for the case of catheter-based interventions. The learning system is augmented with a process that allows a surgeon to watch the robot and provide advice based on the behavior of the robot. In the figure, a catheter surgical robot and the aorta are depicted as examples of a surgical robot and environment, respectively

skill learning ("Surgical skill learning from expert knowledge" section and "Toward autonomous robotic surgery" section) and skill analysis ("Skill analysis in robotic surgery" section) is provided. The robot can learn surgical skills in multiple ways. First, it could learn from its own interaction with the environment, by evaluating the appropriateness of the own actions to reach particular target states. The robot could also learn from human demonstration by observing experiments conducted by expert surgeons. From such demonstration, both the surgical skill and the associated cost function ("Implicit skill analysis" section) used to asses the quality of the displayed skill can be learned. Alternatively, the cost function could also be defined explicitly by the domain expert/surgeon (which is described in "Explicit skill analysis" section). The surgeon could also intervene and guide through observation of robot actions. The information is provided by the surgeon (domain expert), which could then be used to further speed up the learning process. Surgical expertise could also be used to help environment perception. The surgeon can, e.g., teach how to detect natural landmarks or relevant anatomies. This information can help the robot to select adequate (optimal) actions when approaching difficult or risk-prone areas. Some applications of ML in SR are introduced in "Toward autonomous robotic surgery" section.

In the following, we provide a brief introduction to the three important areas of ML: supervised learning (SL), reinforcement learning (RL), and unsupervised learning (UL).

Supervised learning

In SL [24], training data are provided externally and consist of a set of known input vectors along with a set of known corresponding target vectors which might be discrete (classification) or continuous (regression). SL seeks to build a predictor model that predicts reasonable target vectors for new input vectors. The choice of the predictor model is typically up to the designer and often requires considerable ML expertise. Learning consists of finding optimal parameter values for the chosen model. SL could be applied, for instance, in state estimation.

Reinforcement learning

RL deals with learning a *policy*, i.e., a mapping from states to actions. The most popular approaches in RL are value-function- based approaches such as Q-learning [25]. In these approaches, the agent learns the optimal value function of a state action pair. Once the optimal value function is learned, it is possible to generate the optimal policy (skill) for a given task from the value function. Intuitively, a value of a state action pair shows how good it is for the robot (agent) to execute an action in a given state. The training data for RL is generated through direct interaction with the environment and autonomous generation of sequences of experience tuples. An experience tuple is an entry in a training dataset at a particular time which consists of the current state, the current action, the next state and the reward received after executing the action. An important issue in RL is the trade-off between exploration and exploitation: In exploration, the agent tries actions which may be suboptimal according to its current knowledge but has the potential of resulting in better outcomes than expected. In exploitation, the agent always chooses the action which it considers to be optimal at the risk of missing other actions which turn out to be better in reality.

Unsupervised learning

In UL, the training data consists of a set of input vectors without a corresponding set of target vectors. The goal of UL is to discover structure and correlations in the data. Approaches in UL include [24]:

– clustering for discovering groups of similar examples in the data;
– density estimation for determining the distribution of the data;
– dimensionality reduction for data compression, visualization or accelerating subsequent learning.

ML-empowered instrumentation for assisted surgery

Surgical skill learning from expert knowledge

Prior knowledge is of key importance in ML. In surgery, expert knowledge is typically supplied by experienced surgeons. *Implicit imitation learning* is a form of SL, which is usually concerned with accelerating RL through the observation of an expert mentor [26]. The agent observes the state transitions of the experts' actions and uses the information extracted from these observations to update its own states and actions. The mentor (surgeon) and the agent may have identical or different action capabilities, or identical or different reward structures. Several methods that have been developed for modeling human movement (see, e.g., [27]) could be used to learn the state and actions of the expert. Human skill has been modeled from sets of recorded data using hidden Markov models (HMMs) [28,29], neural networks [30,31] and fuzzy nets [32,33].

The work in implicit imitation learning can be categorized into three groups. The first group tries to learn the mentor's policy; the second group learns the reward function of the mentor's behavior and optimizes its own behavior using the learned reward function. The third group employs a Bayesian framework for combining prior (explicit) knowledge and implicit imitation learning. In a series of works, trajectories recorded from human subjects are used to generate an initial policy.

Works on *inverse RL* [34,35] assume that the mentor has the same reward function as the observer and chooses from the same set of actions. The idea is then to infer the reward function of the mentor so as to produce the observed behavior. In other words, inverse RL accomplishes the task of learning both the reward function and the policy (apprenticeship learning).

Bayesian formulations of imitation learning are used to elegantly combine prior knowledge, model observations from the imitator's own experience and model observations derived from other agents. Works in this area developed algorithms for imitation learning that can handle knowledge transfer between agents with different reward structures, learning from multiple mentors and selecting relevant portions of examples [26,36].

Skill analysis in robotic surgery

In optimal control, a skill is the control policy to be designed. Such a control policy is evaluated using a cost or reward function [37]. In surgery, skill evaluation is performed in the context of training and competence evaluation. Training and competence evaluation are now widely recognized as critical for acquiring new clinical techniques or for operating complex devices that are used for patient monitoring or treatment. It is generally accepted that the skill level of clinicians varies and can be enhanced with teaching, training and naturally through experience. Clinical outcomes have in the past been linked to clinical skill [38], and as a result, effective surgical training and evaluation could have a significant impact on healthcare. However, despite advances in simulation, phantom models and task-based procedural trainers, typical training aimed at enhancing manual dexterity and instrument handling still involves significant expert monitoring. This is time-consuming and hence costly to the healthcare system. In addition, it is also, to a certain extent, subjective in nature. It could further be inefficient if real-time feedback of the task performance is missing. Also, for skill learning in SR, skill analysis plays a crucial role, as it can be used as a means to asses or evaluate the quality of the skills that were learned.

Different objective assessment techniques have been reported in the literature. Metrics can be based on task completion time, instrument speed, distances or more complex measures derived from, e.g., position information [39]. Such metrics could be computed directly from robot sensor and motor recordings, or they could be gathered through virtual reality simulators. Simulation environments form an appealing way to enhance understanding and evaluation of skills as they offer full geometric knowledge of the procedure [39,40].

In the following, a distinction is made into explicit and implicit types of SR skill analysis. As an example, where possible, illustrations are given for skill analysis in endovascular procedures.

Explicit skill analysis

In *explicit skill analysis*, the form of the cost function is defined by the domain expert (surgeon). This input can be acquired under different forms.

Checklists and rating scales

Checklists and rating scales form a validated means of assessment. For example, Tedesco et al. let experts appraise seven aspects of performance using a five-point Likert scale [41]. The main concern regarding the use of rating scales is the vast amount of expert time that is required to analyze and score performance (e.g., by observing videos of trainee operations). Efforts to reduce the necessary time by limiting evaluation to 'relevant' parts have been found not to be very reliable [42]. As a result, the current measure of competence in endovascular procedures is still based on a classical view, simply counting the number of procedures performed and time spent in training a respective skill.

Structured assessment

The aim of structured assessment approaches is to attempt to standardize evaluation through rated checklists on a phantom bench-top model. Objective Structured Assessment of Technical Skills (OSATS) is one of the first methods designed for objective medical skill assessment, which aims at quantifying medical skill evaluation without relying on expert evaluators. It consists of a global rating scale and a procedure-specific checklist. OSATS is one of the few methods that has been implemented in clinical practice [43,44].

Nevertheless, even with structured methods, objective assessment of surgical skills is currently underdeveloped. Existing structured grading practices suffer from the need for well-structured tasks and the need for clinical experts to administer the assessment. Added cost and time, and also subjectivity, pose additional problems to the sustainability of structured approaches. Automated and analytical approaches are thus required and need to be researched and validated further.

Outcome-based analysis

In outcome-based analyses, metrics such as the number of complications, morbidity and mortality rates are measured. One assumes that a strong relationship exists between the patient outcome and the skill level [45]. However, this approach suffers from the complication that patient outcomes are also strongly dependent on the patient characteristics, the diagnostic information, the surgical team, the condition and difficulty of the procedure. For example, a less experienced surgeon could be selective and take low-risk cases than a more experienced surgeon. Because of this, the former could display better outcome-based skill measures than the latter. In conclusion, outcome-based metrics are not comprehensively meaningful and do not lend themselves to training and assessment during medical accreditation courses.

Motion analysis

One of the most promising methodologies for task and manual dexterity evaluation is motion analysis. In motion analysis, the surgeon's hand or tool motions are recorded and analyzed by different instruments such as Imperial College Surgical Assessment Device (ICSAD), the Advanced Dundee Psychomotor Tester (ADEPT), the ProMIS Augmented Reality Simulator, the Hiroshima University Endoscopic Surgical Assessment Device (HUESAD) and the TrEndo Tracking System [41,46–50]. The technique can provide a good assessment of dexterity and technical skill level, but it has not been used or investigated thus far for endovascular procedures [42]. Nevertheless, this methodology has the most abundant literature references [42], especially with recent technological developments in robotics and particularly the da Vinci API [51,52]. Multiple studies have shown that skill metrics can be derived using statistical analysis (HMM [28,53,54]) of instrument motion from this data [55].

Time action analysis

Time action analysis is a technique where the surgical procedure is broken down into several steps, and the time to complete each one is measured (usually by an expert watching a video recording of the exercise). The limitation of this approach is apart from being time- consuming, and it does not report any measure of how well the particular surgical action was performed [56]. While not particularly informative about what the failings or technical limitations of a particular task are, time action analysis does offer a simple means of evaluation and can often be linked or correlated to clinical competence. The problem lies in identifying when a performed task is done badly or with considerable potential risk to the patient (or benchtop environment).

Virtual reality

An emerging training modality is Virtual Reality (VR). VR potentially offers a vast amount of valuable information for assessment and analysis of different surgical techniques [57]. The validity of VR in endovascular procedures is still under evaluation. So far, the endovascular surgery simulators that are available on the market have only to a limited extent been integrated into the training curriculum or for formal accreditation, but it is likely that simulators will play an increasingly important role in surgical training.

Error analysis

Error analysis, where the number of errors made during certain part of the procedure is scored, is an alternative and potentially more thorough skill evaluation technique. For endovascular surgery, errors can be defined by, for example, the number, location or intensity of the contact with the vascular wall. Such parameters could be recorded by some simulation systems [46]. However, to the knowledge of the authors, no in vivo or phantom study, taxonomy of errors or scores exist at this point including these parameters. It seems that this metric ought to be investigated since the vessel wall provides a geometric enclosure for the tool, and therefore, errors can be evaluated easily [58].

Implicit skill analysis

Implicit skill analysis uses a metric which is learned by an ML approach from a surgeon or group of surgeons. The learned metric can then be used to evaluate other surgeons (trainees) relative to the skills of a surgeon (surgeons) from which the metric is learned.

Classification of surgical skill levels

Reiley et al. [59] applied Vector Quantization (VQ), a UL approach, and HMM to evaluate the skill from continuous velocity data of the da Vinci system. In Reiley's paper, HMMs based on skill are developed for three surgical levels such as novice, intermediate and expert. In the paper, it is shown that HMMs are important methods to classify skill of unknown trial based on maximum likelihoods from trained skill models of novice, intermediate and expert surgeons.

An automatic method of parsing raw motion data from a surgical task from a labeled sequence of surgical gestures that would allow for the development of automatic evaluation of surgical skills is developed by Lin et al. [60]. The method has feature processing and classification steps where a Bayes classifier is used for the classification step. Results show that the method is able to correctly identify the different gestures for the case of a suturing task using the da Vinci surgical robot against benchtop models. It has been shown that based upon the analysis of instrument motions it is possible to distinguish an expert surgeon from a surgeon having limited da Vinci experience. The method is further extended to handle data from live surgeries and for more number of users [61].

Rafii-Tari et al. [62] proposed a learning-from-demonstration framework for robot-assisted cardiac catheterization. The motion model of the catheterization procedure is trained by manipulations from experts and intermediate-level operators. The motion model is represented by a Gaussian Mixture Model (GMM) and clustered by the k-means algorithm. Then Gaussian Mixture Regression (GMR) is used to smooth the motion trajectory. For validation, the same procedure is performed by novices assisted by a robotic catheter driver. A significant difference between skills of novices and skills from experts and intermediate-skilled operators was observed.

Surgical workflow analysis and episode segmentation

A surgical procedure is in essence a concatenation of surgical acts, which when pertaining to the same specific surgical (sub)goal can be grouped into surgical (sub)tasks. *Workflow Analysis* can be conducted to identify the different surgical (sub)tasks that belong to a surgical intervention, the order in which (sub)tasks can follow each other and possible termination conditions that mark transients between distinct (sub)tasks. The analysis of the surgical workflow is essential to assist surgical navigation and enable the design of cognitive surgical systems that can adapt and operate in highly dynamic environments such as the cardiovascular system. In addition, the analysis of individual surgical tasks can provide quantitative evaluation of surgical skills during different procedural tasks.

Thus far, the analysis of surgical workflow has been extensively studied for minimally invasive procedures. Approaches proposed in the literature can be classified into methods for segmentation of high-level surgical tasks (surgical phases) and methods for the recognition of low-level tasks (surgical gestures) and into off-line and online approaches.

In [63,64], laparoscopic cholecystectomy procedures are segmented into 14 different phases based on the presence of instruments in the surgical scene. AdaBoost is used in [63] to analyze the use of each surgical instrument in each phase of the surgery and weight them according to their discriminative power. For phase recognition, an average reference surgery is generated based on Dynamic Time Warping (DTW) and used to segment newly observed procedures.

A significant number of approaches to surgical gesture recognition focused on modeling kinematic data with HMMs using a variety of methods for modeling the observations such as vector quantization of the observations into discrete symbols [65], Gaussian HMMs combined with Linear Discriminative Analysis (LDA) [66], Factor Analyzed HMMs (FA-HMMs) and Switched Linear Dynamical Systems (SLDSs) [67]. Sparse HMM has been used in [68] where the observations are modeled as sparse linear combinations of basic surgical motions. In [69], tool–tissue interactions of a knot-tying task in MIS have been modeled using Markov Models (MM) based on the kinematics (position and orientation) and the dynamics (force and torque) of the surgical tools.

Toward autonomous robotic surgery

The role of ML in autonomous robotic surgery

When profound and up-to-date understanding of a surgical task is available and when a robotic system has demonstrated repeatedly its ability to correctly display an acceptable

Table 1 Aspects of autonomous robotic surgery (ARS) where ML could play an enabling role

Workflow analysis episode segmentation	Surgical procedure broken down into logical subtasks or episodes
Environment modeling	Rigid and flexible registration, reconstruction of environment, recognition of anatomical features and landmarks, mechanical and physiological modeling
Localization	Localization of instrument/robot w.r.t. environment
Robot control	Low-level modeling and robot control
Skill analysis	Analysis of surgical skill, derivation of performance metrics or cost functions for optimization
Critical event detection	Detection of adverse events
Planning and control	High-level trajectory and interaction planning, error handling

level of performance in executing the necessary surgical acts under similar surgical conditions, one might consider to let the robot perform these surgical gestures in an autonomous fashion. Different technologies introduced in preceding sections could serve here as building blocks. These blocks could for example be plugged into the framework proposed by Muradore et al. [19] who follow a model-based approach. This means that the entire procedure and its different components are explicitly modeled. An ML-based variant of this approach could also be envisaged. In such case, models of the procedure, environment, instrument, etc., could be constructed and learned directly from the data. Table 1 summarizes the different aspects that could be covered in such case.

For an excellent review on works on autonomous and semiautonomous robotic surgery, we gladly refer to the work by Moustris et al. [70]. Table 2 shows that robotic autonomy has been studied in a very broad set of surgical domains. A number of papers are reported to be generally applicable across domains or introduce general frameworks to support ARS. The second part of the Table shows that substantial efforts have been done to automate a wide range of surgical gestures. Figure 2 gives a fair idea of the evolution in ARS (despite being based on a non-exhaustive set of ARS papers). It can be seen that the number of papers dealing with ARS is steadily growing over time. Furthermore, when looking at the share of ARS papers that employ ML techniques, one can appreciate that also this share grows accordingly. A detailed discussion of each of these works falls outside the scope of this work, rather it is opted to discuss a selection of works in more detail in the following section.

Examples of ML used in SR research

Intelligent autonomous endoscopic guidance system

Modern laparoscopic surgery or MIS procedures make use of three or four access ports through which a plurality of instruments is inserted in the body. Typically, this includes an endoscope that is used to visualize the patient's organs alongside instruments for grasping, cutting, ablating and so on. Casals et al. [96] a.o. conducted research to automatically steer laparoscopes in such configuration. In order for such tracking system to behave in an automatic fashion, steering must be extremely reliable. This implies that such system should be capable of tracking all aspects of the procedure and in a robust fashion. In contrast to the short-term prediction, steps associated with typical control schemes that focus on the compensation of physiological motion such as heartbeat and breathing [99,107,116,154], Weede et al. [100] advocate the development of *long-term* prediction schemes that anticipate upon what the surgeon is going to do during the next couple of minutes, so that the endoscope can always be moved to an appropriate position. To this end, Weede et al. proposed an intelligent endoscopic guidance system (Fig. 3). The system collects information on the movements of the instruments from former interventions and predicts based on this knowledge trajectories that are used to autonomously guide the endoscopic camera. The knowledge is extracted by trajectory clustering, maximum-likelihood classification and a Markov model to predict the procedural states. Although encouraging results were reported, a better understanding of the ongoing tasks and the surgeon's intent were mentioned as possible ways to further improve the system response.

Autonomous knot-tying

Surgeons frequently have to tie knots to connect tissues or close openings. In MIS, where access and maneuverability are limited and haptic feel is typically poor if not absent, knot-tying is a tedious job. Whereas in open surgery a knot can be tightened within a few seconds, in MIS this can take up to three minutes per knot [115]. As a consequence, many research has been conducted to automate suturing and knot-tying, which is also evident from Table 2. Research was also conducted to apply ML to solve suturing and knot-tying. For example, Mayer et al. published a series of works to this end [115,118,119,121].

Table 2 Classification of publications dealing with ARS

Surgical discipline	All	Soft tissue	Interaction	ML
Neurosurgery	[10, 12, 71–73]	[10, 12, 71–73]	[10, 71, 72]	[72]
Orthopaedic surgery	[74–78]		[74–76, 78]	
Craniofacial	[79, 80]			
Cochleostomy	[20, 81–83]		[20, 81–83]	
Radiosurgery	[13, 84, 85]	[13, 84]		[85]
Cardiac/vascular	[21, 86–88]	[86–88]	[86]	[21, 86]
Catheter procedures	[89–91]	[89–91]	[89–91]	
Urology	[92–95]	[93–95]	[94]	
Abdominal	[96–112]	[97–99, 101, 102, 104–109]	[98, 99, 102]	[97, 100, 103]
Colonoscopy	[113]	[113]		
Anestesia	[22]			
Surgical technique	**All**	**Soft tissue**	**Interaction**	**ML**
Knot-tying, suturing	[9, 14–16, 87, 114–126, 128]	[9, 14–16, 87, 114–126, 128]	[9, 14, 16, 115, 118–122, 124–128]	[9, 115, 116, 118–122, 125]
Biopsy, needle placement, piercing	[19, 72, 129–136]	[19, 72, 129–136]	[72, 129, 130, 133, 136]	[72]
Tissue retraction	[17, 18]	[17, 18]	[17, 18]	
Palpation	[136–138]	[136–138]	[136–138]	[137, 138]
US tracking	[139–141]	[139, 140]	[139, 140]	
Scanning	[142, 143]	[142, 143]	[142, 143]	[142, 143]
Ablation	[144]	[144]	[144]	[144]
Debridement	[145]	[145]		
Tool exchange	[146]	[146]		[147]
General framework	[19, 148, 152]	[149, 150, 152]	[151, 152]	
General purpose	[79, 153]			

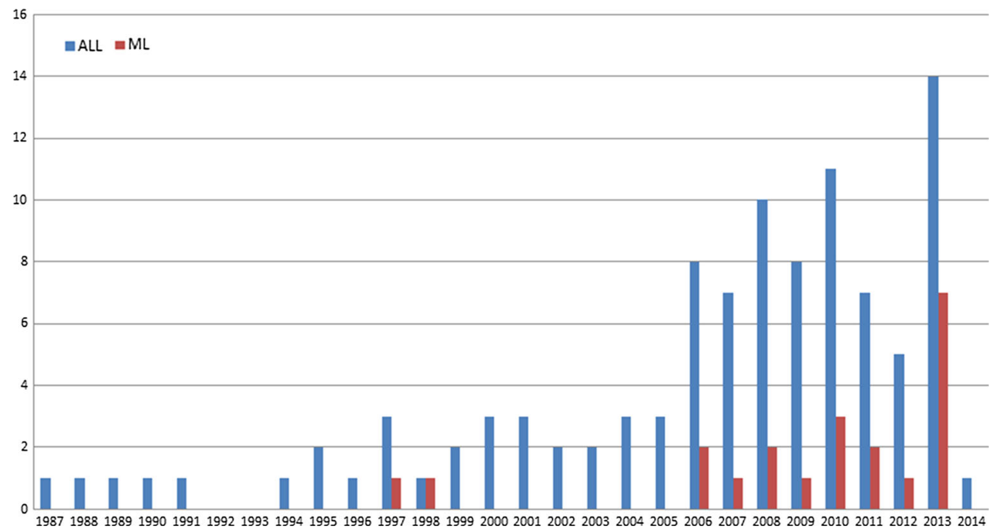

Fig. 2 Evolution of a reference number of publications regarding ARS over the years. The number and share of papers employing ML can be seen to rise over time

Fig. 3 Prototype robotic system for MIS, two KUKA LWR IV robots with attached grasper, Stäubli RX90 with attached endoscope, force dimension omega.7, haptic interface and pelvis trainer [100], Courtesy of Karlsruhe Inst. of Technol

Knot-tying with neural network

For instance, Mayer et al. [115] used recurrent neural networks (RNN) to tie knots autonomously. The system is reported to speed up the knot-tying, reducing the overall time of the surgical intervention. A sequence is presented to the network by a surgeon after which the sequence is learned. A neural network with long-term storage [155] is used to learn this task. Only after a few sequences, the network is capable of performing the basic steps.

Knot-tying via trajectory transferring

Schulman et al. [125] developed recently a trajectory transfer method, which can tie knots in ropes by training the robots by human demonstration. During the procedure, a nonrigid transformation from training state to the testing state is registered. Based on the transformation and the training trajectory, the new trajectory for the testing task can be calculated. Five different types of knots were automated.

Superhuman performance of surgical tasks

Van den Berg et al. [9] developed an algorithm that learns a task from multiple human demonstrations. The algorithm learns to execute the tasks with superhuman performance. The important parameters maximized during the learning process are smoothness and speed of task execution. The approach is implemented on the Berkeley Surgical Robot and applied to two tasks: first drawing figures on a magnetic wire-boards and second knot-tying.

Skill transfer from surgeon teleoperator to flexible robot

Recently, Calinon et al. [156] developed a method based on inverse RL [34,35] for transferring skills from a surgeon teleoperator to a flexible robot. The flexible robot is a bio-inspired robot that mimics the way octopuses elegantly move through small openings and difficult environments. The method can handle the case where robots used for transferring skills have different morphological structures.

GMM-/GMR-based learning from demonstration

In recent papers [86,142,143], GMM algorithms are used to learn from demonstration by representing datasets stochastically using joint probability densities. Kassahun et al. [86] developed a method to learn the model of the interaction between catheter and aorta. GMM is used to model the joint probability densities of the multiple variables which are used to represent the catheter shape, touching states, entrance and tip points of the catheter. It has been shown that it is possible to predict the shape of the catheter only by knowing catheter entrance and tip points.

Potential applications of ML in SR

In addition to above-mentioned works, ML can be used broader for different purposes in SR. In this section, future envisioned applications of ML in SR are given.

Automation of the surgical operation

The operating room (OR) is densely populated with different surgical equipments and the surgery team can be quite large. Therefore, the amount of information that is generated can be quite impressive. A surgeon's ability to process all the available information and at the same time establish and sustain an appropriate level of situation awareness is limited and also surgeon dependent [157,158]. The cognitive load could potentially be reduced by employing ML techniques. Based on knowledge of the procedure workflow, such techniques could provide information and guidance, signaling critical events. Ultimately, such techniques could take over repetitive and time-consuming tasks. ML techniques could steer surgical robots to safely, accurately and possibly at faster speed execute some specific surgical tasks. It has already been shown that the time taken by a surgical procedure can be reduced using a robotic scrub nurse [159]. Apart from reduced operation time, enhanced performance and reduced miscommunication could be achieved.

Training surgeons

In current surgical practice, trainees are mainly under the supervision of senior surgeons and surgical skills are also evaluated based on the experiences of the supervisors. Therefore, the experience of senior surgeons is used as evaluation criteria. Such evaluation criteria are, however, not always as accurate and have not been adequately quantified (see "Skill analysis in robotic surgery" section). ML approaches have the potential to learn a statistical model of surgical skills of experienced surgeons from data collected in the OR [122]. The learned surgical skills could be used for quantitatively evaluating surgical skills of trainees. Moreover, ML techniques could be used to improve existing trainers by accurately modeling the interaction amongst surgeons, patients and surgical instruments (robots).

Classification and standardization of medical practice

At present, it is difficult to compare and evaluate different medical therapies that are performed by different surgeons and in different hospitals. For reducing the costs and improving quality of healthcare, a standardization system identifying best medical practice is desired. The main challenge exists in classifying the variety of the skills of different surgeons. ML techniques are able to develop a statistical model, splitting the surgical technique into different steps, learning per step the best medical practice from all of the surgeons for a given situation. Such knowledge could be continuously and automatically updated as more data becomes available.

Saving the best strategies of an experienced surgeon

ML can be used to learn the skills of an experienced surgeon and save it for later use in the OR or to train young surgeons. It can be used to initialise newly introduced robotic systems that can start from such basic knowledge after which they can continue translating and refining this information toward the own actions. Moreover, ML techniques such as decision trees and forests, artificial neural networks, Bayesian networks, Support Vector Machines and Gaussian processes [160] could discover and evaluate operating techniques that do not yet belong to, but could potentially outperform current surgical practice.

Safe interaction between environment and surgical robots

ML could be further used to model the environment (patients) in greater detail or to identify some specific features such as anatomic landmarks, mechanical or physiological properties of the environment. In robotically assisted surgery, accurate perception of the surgical environment is essential to the control and decision- making process to find out how to interact safely within a fragile dynamic environment or how to explore such an environment in the presence of high uncertainty about its properties.

Safe interaction between surgeons and surgical robots

In a similar way, ML could help guaranteeing the safety of surgeon. For an example, by defining dynamic active constraints [161], it is possible to design impedance controllers that guarantee safe human–robot interaction, while at the same time allowing the definition of a safe workspace for the robot. Safety can also come from the design of soft and highly compliant robots or by remotely control of surgical robots. ML can help to design both low- and high-level controllers for these elements.

ML for SR: challenges and directions for further work

While ML is receiving more attention in surgery and robotic surgery in particular, its use in current surgical practice is still very limited. In the following, a number of challenges that need to be faced by the research community are listed concisely.

High-quality medical/surgical data

There is a need for large quantities of high-quality medical and surgical data to train ML techniques. Data is to be obtained following well-described protocols and stored in standardized formats to ensure interoperability and correct use. In case non-traditional imaging or data-capturing modalities are being used, i.e., requiring actions or sensing that deviates from current standard clinical practice, approval by an Ethical Commission might be required. Furthermore, measures should be installed to ensure protection of patient's privacy.

Modeling challenges

The major challenge in modeling the surgical environment is the dynamic and deforming nature of the living body which restricts the use of preoperatively estimated 3D maps and requires the analysis of intraoperative data. For that purpose, geometric, mechanical and physiological behavior of the environment should be considered However, fusion of multiple sensors is not trivial as it involves theoretical and technical challenges such as sensor co-registration, synchronization and information fusion. On top of that, the modeling of the deformation of the environment due to physiological phenomena such as respiratory motion and heart beat is to be incorporated.

Learning and defining skill analysis metric

An important problem in learning skill analysis is to come up with metrics that adequately capture the characteristics of best practice. Because of variations in procedure and practice, the learned skills could only be applicable to a certain group of cases and surgeons. A major challenge is thus to learn a sufficiently general skill metric that can be applied across different groups of surgeons. Moreover, the definition of a metric that guides the execution of a surgical act is difficult. Depending on the structure of the solution space, a given cost function may not lead to the optimal performance.

Adaptation to unknown or yet unobserved situations

Any system deployed in the OR and given decision-making power should be able to cope with uncertainty and unpredictable events and guarantee the safety of the patient just as expert surgeons have to adapt to such situations. The development of algorithms that are able to adapt the learned skill to novel (unexpected) situations is an important challenge. In this line, transfer learning aims at reducing the need of recollecting the training data, and improving learning in the new task by transferring the knowledge between different task domains.

Pipeline for training and deploying autonomous surgical action

Given the large complexity and multidisciplinary nature of the surgical intervention and its automated counterpart, there is a need for a structured approach to efficiently transfer surgical skill toward automated execution. The envisioned framework would guide the skill transfer over all aspects of the surgical procedure, providing tools and guidance to:

– analyze the surgical workflow, query surgeons to identify procedures or parts of procedures for which automation would be of interest;
– set up the surgical scene for gathering data, providing documentation and directions to apply for approval at respective ethical regulatory bodies;
– gather, represent and store data in exchangeable and standardized formats;
– segment, filter and preprocess data for delivery to ML algorithms;
– extract surgical skills and associated reward functions from surgical data;
– train models and controllers to replicate or improve upon surgical skills. This can take place autonomously or through human demonstration and interaction with surgeons;
– evaluate robustness and transferability of learned skills;
– program robotic actions that display a targeted surgical skill;
– analyze the scene and interaction to detect transitions or inconsistencies, triggering appropriate robotic actions, event or error-handling methods;
– evaluate overall performance in an autonomous manner or by clinical experts.

Conclusion

This paper reviewed the different building blocks and research activities in adopting ML methods for SR. The paper demonstrated that ML can play a role in many aspects of SR. Synthesizing and exploiting the knowledge and experience of surgeons requires a thorough understanding and analysis of skill, training and evaluation. By detailed study of the surgical process, it may be possible to extract the needed mappings from perception to action (imitation learning) for various surgical tasks and meanwhile quantitatively analyze learned skills. By subdividing surgical procedures into individual surgical tasks through episode segmentation, the process can become manageable. A detailed pipeline for deploying ARS is proposed. This starts from a workflow analysis that decomposes the procedure into episodes. For each episode, the desired behavior can be learned as skill. This information is to be embedded within the surgical robot's control loop equipped with appropriate decision-making mechanisms that help deploying the appropriate skill at the appropriate time. As such, surgical robots could gain autonomy over time, resulting into semi-autonomously or fully autonomously operating systems in the future.

Whether autonomous surgical robots will really break through depends on many factors as the challenges to overcome are substantial. There should be access to large amounts of high-quality medical/surgical data. Progress is needed w.r.t. modeling and real-time evaluation of deformable anatomies. There is still much to be learned on what is exactly a surgical skill and how to quantitatively analyze it. Better understanding is needed on how to adapt systems reliably and safely to unknown or previously unobserved situations. Besides those challenges, getting the acceptance and trust of the physicians and patients is considered a not to be underestimated challenge as well.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent This article does not contain patient data.

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