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Advancements in Deep Learning for Minimally Invasive Surgery: A Journey through Surgical System Evolution

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ABSTRACT

The surge in artificial intelligence (AI) applications across diverse fields owes much to advancements in deep learning and computational processing speed. In medicine, AI's reach extends to medical image analysis and genomic data interpretation. More recently, AI's role in analyzing minimally invasive surgery (MIS) videos has gained traction, with a growing body of research focusing on organ and anatomy identification, instrument recognition, procedure recognition, surgical phase delineation, surgery duration prediction, optimal incision line identification, and surgical education. Concurrently, the development of autonomous surgical robots, exemplified by the Smart Tissue Autonomous Robot (STAR) and RAVEN systems, has shown promising strides. Notably, STAR is currently employed in laparoscopic imaging to discern the surgical site from laparoscopic images and is undergoing trials for an automated suturing system, albeit in animal models. This review contemplates the prospect of fully autonomous surgical robots in the future.

Introduction:

There is no universally accepted definition of artificial intelligence (AI), but it generally refers to computer systems endowed with capabilities akin to human intelligence, such as learning, inference, and judgment. Machine learning involves the technology wherein computers assimilate vast amounts of data to autonomously construct algorithms and models for tasks like classification and prediction. The evolution of AI has been propelled by the advent of deep learning, a machine-learning technique that harnesses neural networks arranged in multiple layers to enhance expression and learning capacity. Deep learning has found applications in image recognition, facilitating tasks like face recognition and automated driving.

The fusion of robotics and AI offers manifold advantages in everyday life, endowing robots with the ability to sense their environment and make decisions accordingly. In the medical realm, AI is making significant inroads, particularly in image recognition. Prior research has demonstrated AI's proficiency in diagnosing diseases by analyzing various medical images like X-rays, CT scans, and ultrasound images through deep learning algorithms. Furthermore, deep learning techniques have been employed to diagnose diseases and forecast patient outcomes based on data from medical records.

The adoption of minimally invasive surgical techniques has become widespread across various surgical disciplines. Notably, the scope of robot-assisted surgery systems such as da Vinci has expanded in recent times. Concurrently, there has been a surge in studies utilizing deep learning to analyze surgical videos and apply insights to medical care. Moreover, a growing body of research focuses on the development of autonomous surgical robots.

This review aims to explore the potential of fully autonomous surgical robots in the future. Initially, it discusses studies leveraging deep learning to analyze surgical videos in laparoscopic and robot-assisted surgeries. Subsequently, it delves into research concerning the development of autonomous surgical robots powered by AI.

Laparoscopic Surgery Video Analysis Using Deep Learning

The development of autonomous surgical robots hinges significantly on the accurate recognition of surgical intricacies. Numerous studies have employed deep learning techniques for laparoscopic surgery and robot-assisted surgery. Different facets are elucidated below:

Organ and Instrument Identification:

Previous research has elucidated the identification of organs and anatomical structures in laparoscopic images through deep learning methodologies. Zadeh et al manually annotated gynecological laparoscopic videos to identify the uterus, ovaries, and surgical instruments using Mask Regional Convolutional Neural Network (Mask R-CNN). However, segmentation accuracy varied, with ovary identification being particularly challenging due to its often obscured presence and varying appearance across patients. Mascagni et al developed a deep-learning model to automatically segment the liver and gallbladder in laparoscopic images, crucial for laparoscopic cholecystectomy (LC). This model facilitated the identification of the critical view of safety (CVS) by accurately highlighting anatomical landmarks. Padovan et al utilized deep learning from laparoscopic surgery videos to construct 3D models, achieving accuracy exceeding 80% in all tests. Such models aid in preoperative simulation and augmented reality-assisted surgery, enhancing surgeons' spatial understanding and decision-making.

Surgical Instrument Identification:

Several studies have addressed the identification of surgical instruments during laparoscopic procedures. Namazi et al developed LapToolNet, an AI model capable of detecting various surgical instruments with agreement rates exceeding 80% in each frame of a laparoscopic video. Similarly, instrument recognition studies have been conducted to assess surgeons' skill levels and surgical technique variations. Notably, deep learning models have been employed to evaluate surgical skills by analyzing instrument usage patterns during procedures like laparoscopic gastrectomy for gastric cancer.

3. Real-time Feedback and Educational Applications:

Deep learning models have been utilized to provide real-time feedback on surgical technique and instrument visibility. For instance, Aspart et al developed a deep-learning model to assess the visibility of the clip applier during cholecystectomy, offering valuable insights into surgical proficiency. Such analyses serve as educational tools, enabling the identification of optimal surgical practices and facilitating skill enhancement through targeted feedback mechanisms.

In summary, the application of deep learning in laparoscopic surgery video analysis encompasses various aspects, including organ and instrument identification, safety assessment, and skill evaluation, with potential implications for both surgical practice and education.

Table I. Previous studies on surgical-related artificial intelligence analysis.

Authors	Year	Procedure	Dataset	No.	Application	Performance score	(Refs.)
Zadeh *et al*	2020	Gynecologic surgery	Mask R-CNN	461 images	Organ identification	Accuracy:29.6% (ovary) and 84.5% (uterus)	(10)
Mascagni*et al*	2022	Laparoscopic cholecystectomy	CNN	2,854 images	Organ identification	Average accuracy: 71.9%	(13)
Padovan *et al*	2022	Urologic surgery	Segmen-tation CNN	971 images	Organ identification	IoU: 0.8067 (prostate) and 0.9069 (kidney)	(14)
Koo *et al*	2022	Liver surgery	CNN	133 videos	Organ identification	Precision: 0.70-0.82	(15)
Namazi*et al*	2022	Laparoscopic cholecystectomy	Recurrent CNN	15 videos	Instrument identification	Mean precision: 0.59	(16)
Yamazaki*etal*	2022	Laparoscopic gastrectomy	CNN	19,000 images	Instrument identification	N.A.	(17)

Aspart*et al*	2022	Laparoscopic cholecystectomy	CNN	122,470 images	Instrument identification	AUROC: 0.9107; specificity66.15%; and sensitivity: 95%	(18)
Cheng *et al*	2022	Laparoscopic cholecystectomy	CNN	156,584 images	Surgicalphase recognition	Accuracy: 91%	(19)
Kitaguchi*et al*	2022	Transanaltotal mesorectal excision	CNN	42 images	Surgicalphase recognition	Accuracy: 93.2%	(20)
Kitaguchi*et al*	2020	Laparoscopic sigmoid colon resection	CNN	71 cases	Surgicalphase recognition	Accuracy: 91.9%	(21)
Twinanda*etal*	2019	Cholecystectomy and gastric bypass	CNN and LSTM network	290 cases	Surgical time prediction	N.A.	(23)
Bodenstedt*et al*	2019	Laparoscopic interventionsof varioustypes	Recurrent CNN	3,800 frames	Surgical time prediction	Overall average error: 37%	(24)
Igaki*et al*	2022	Totalmesorectal excision	CNN	600 images	Safe surgical navigation	Dice coefficient: 0.84	(25)
Kumazu *et al*	2021	Robot-assisted gastrectomy	CNN	630 images	Safe surgical navigation	N.A.	(26)
Moglia*et al*	2022	Virtualsimulator for robot-assisted surgery	CNN	176 medical students	Surgical education	Accuracy: >80%	(27)
Zheng *et al*	2022	Box trainer for laparoscopic surgery	Long-/ short-term memory recurrent neural network	30 medical students	Surgical education	Accuracy: 74.96%	(28)

In another investigation, Kitaguchi et al engineered a model employing CNN-based deep learning to discern the steps and procedures involved in laparoscopic sigmoid colon resection. This model, trained on manually annotated data, achieved a recognition accuracy of 91.9%. Indocyanine green, utilized to assess blood return after bowel resection and anastomosis in endometriosis, served as the focus of another study. Here, a prediction model for blood return post-anastomosis was formulated through deep learning analysis of indocyanine green-injected bowel images. Predicting surgical time is pivotal for effective scheduling, although fewer studies have explored this aspect using AI. Twinanda et al developed RSDNet, a deep-learning pipeline enabling real-time prediction of remaining intraoperative surgical time solely through visual information extracted from laparoscopic images.

Bodenstedt et al devised a convolutional neural network-based method for continuous laparoscopic surgery time prediction using endoscopic images. Despite an overall average error rate of 37%, this approach marks progress towards developing surgical navigation systems and autonomous surgical robots by capturing changes in higher-order features, such as surgical procedures.

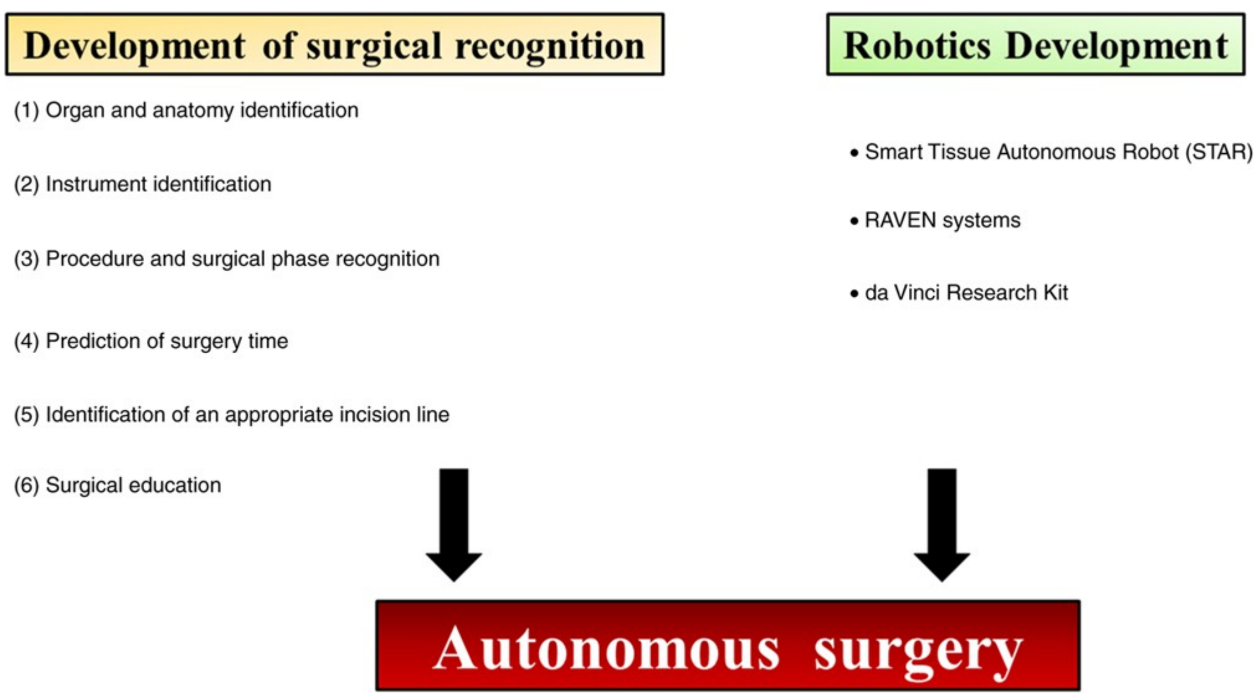
Surface navigation systems for ensuring safe incisions have garnered attention, with AI playing a pivotal role. Igaki et al pioneered AI-based navigation of the entire mesorectal resection plane in laparoscopic colorectal surgery.

Meanwhile, Kumazu et al developed a model for automatic segmentation of loose connective tissue fibers (LCTF) using U-NET-based deep learning. Surgeons' responses suggested AI's potential in recognizing intricate anatomical structures, highlighting its role in assisting surgeons during surgery.

In the realm of surgical education, deep learning finds application in predicting medical students' proficiency in surgical simulators. Moglia et al utilized deep learning to forecast proficiency levels with an accuracy rate exceeding 80%. Additionally, Zheng et al developed a real-time deep-learning model capable of detecting stress-induced movements during surgical procedures. This stress-sensitive procedure identification holds promise for integration into robotic-assisted surgical platforms and stress management techniques.

The ongoing development of such systems underscores the potential for leveraging deep learning in surgical education and practice, paving the way for enhanced surgical outcomes and stress management strategies.

Autonomous Surgical Robots



Defining Autonomy: Autonomy, commonly associated with independence and decision-making capabilities, lacks precise standards and is often misused. For instance, the da Vinci system, widely used in hospitals, is erroneously labeled a surgical robot despite functioning primarily as a high-tech motion repeater manipulator. To avoid such misnomers, defining autonomy becomes crucial when developing autonomous surgical systems. Han et al. and Yang et al. proposed six frameworks akin to those for autonomous vehicles, delineating levels of autonomy for medical robots.

1. Level 0 - No Autonomy: Surgical robots with motion scaling capabilities, responding to surgeon commands.

2. Level 1 - Robotic Assistance: Robots providing assistance while surgeons predominantly manage the system.

3. Level 2 - Task Autonomy: Robots autonomously performing specific tasks initiated by humans, with discrete operator control.

4. Level 3 - Conditional Autonomy: Robots capable of system-generated task execution, relying on humans to select among different plans.

5. Level 4 - High Autonomy: Robots capable of decision-making in surgery but only under qualified physician supervision.

6. Level 5 - Full Autonomy: Robots performing entire surgeries without human intervention.

Considerations for Autonomous Surgery: Two crucial factors, Recognition and Task, determine the autonomy level. Recognition involves awareness of the environment, understanding current status, and predicting future status. Task complexity ranges from simple training tasks to complex surgical maneuvers like suturing or managing sudden bleeding. Development efforts for autonomous surgical robots must align with these classification levels.

Current Autonomous Surgical Robots: Despite the widespread adoption of robot-assisted surgery, procedures on soft tissues are predominantly manual. Shademan et al. introduced the Smart Tissue Autonomous Robot (STAR), a supervised surgical robot capable of executing complex surgical procedures previously limited to human surgeons. STAR marks a significant advancement in achieving autonomy in surgical robotics.

The primary objectives of the Smart Tissue Autonomous Robot (STAR) were to perform anastomosis and suturing, crucial techniques for various soft organ surgeries like those involving the intestinal tract, urinary system, and gynecological vaginal segments. These procedures demand repeatability, accuracy, and efficiency, thus driving the development of autonomous surgical robots. Autonomous robotics surgery offers advantages in efficacy, safety, and reproducibility, irrespective of individual surgeon skill levels.

Anastomosis poses a challenge for autonomy due to its need for complex imaging, navigation, and precise execution. STAR achieved intestinal anastomosis in open surgery in pigs by employing a 3D visual tracking system using near-infrared fluorescence imaging and an automated suture algorithm. Comparisons with robot-assisted and manual laparoscopic surgery showed STAR's superiority in suture consistency, anastomotic leak pressure, mistake count, and completion time. Since then, STAR has undergone numerous improvements, including the development of an autonomous 3D path planning system utilizing biocompatible near-infrared markings for precise incisions in complex soft tissues.

Further enhancements include 3D imaging endoscopy and the creation of a laparoscopic suture tool for automated anastomosis planning, which demonstrated 2.9 times higher accuracy than manual suturing. However, performing anastomosis autonomously presents challenges due to soft tissue irregularities and unpredictable deformations. To address this, Kam et al. developed a new 3D path planning strategy for STAR, enabling semi-autonomous robotic anastomosis in deformable tissues. Comparative experiments showed significant improvements in suture spacing and bite size consistency compared to manual performance.

STAR was also employed to devise shared control strategies for human-robot collaboration in surgical scenarios, resulting in improved cutting accuracy and reduced operator work time. The latest study introduces a novel in vivo autonomous robotic laparoscopic surgical technique characterized by tissue tracking, interaction with humans, and execution of complex surgical plans. This enhanced autonomous strategy surpasses skilled surgeons and robot-assisted techniques in needle placement compensation, suture spacing, completion time, and intestinal suture failure rate. Notably, STAR demonstrated the capability to perform subperitoneal surgery, showcasing its versatility. However, challenges remain regarding its potential automation of incision and hemostasis, as its focus has primarily been on suturing.

A prototype medical robotic system called the RAVEN-II system has been developed with the aim of autonomously detecting and removing residual brain tumors following conventional surgery. This system is designed for scenarios where the majority of the tumor has already been removed, leaving a cavity roughly the size of a ping-pong ball. Equipped with a multimodal scanning fiber endoscope, a suction machine for blood removal, and multiple robotic arms with tissue resection devices, the RAVEN-II system conducts an automated surgical procedure in six distinct subtasks:

1. Medical image acquisition involves scanning the surgical cavity post-tumor removal.

2. Medical image processing includes constructing a 3D representation of the surgical cavity and identifying any residual tumor.

3. Ablation plan creation.

4. Surgeon selection of the plan.

5. Execution of the plan by the robot.

6. Verification of the ablation results.

Another experimental system, the da Vinci ResearchKit (dVRK), represents a collaborative effort between industry and academia to repurpose the outdated da Vinci system (Intuitive Surgical, Inc.) as a research platform for advancing surgical robotics research. This initiative aims to lower barriers to entry for new research groups in the surgical robotics field. For instance, in the dVRK's master tool manipulator, hysteresis forces stemming from the electrical cables of the robotic joints often pose challenges for accurate parameter estimation in gravity-compensation models.

Ensuring full transparency poses a challenge, particularly regarding algorithms, due to the inherent 'blackbox' nature of deep-learning systems and the non-disclosure of source code for copyright and trade secret protection. This lack of transparency undermines trust in robots among physicians and patients. Another concern pertains to the responsibility for the system's use. Who bears responsibility for surgical complications caused by an autonomous surgical robot? In cases of anomalies like loss of communication during teleoperation, who should be held accountable? One proposed solution suggests the surgeon remaining in the same room as the surgical robot, allowing physician control at all times. Alternatively, employing a limited system that assists rather than fully automates routine surgery is another option. Discussions on ethical and regulatory considerations should be concluded by the time an autonomous surgical robot is developed, ensuring safety and consistent performance surpassing that of a human surgeon.

Conclusion

While the realization of fully autonomous surgical robots in clinical settings may still be on the horizon, the prospect of partially autonomous systems appears promising in the near future. Advancing surgical recognition and robotics through deep learning, particularly leveraging surgical videos, is key to this progress (Fig. 1). This review explored various studies on surgical video recognition, encompassing organ and surgical instrument identification, as well as surgical education. Among these tasks, the accurate identification of the resection site emerges as paramount. However, current AI models' accuracy falls short of clinical application standards. The ultimate aim is for physicians to safely conduct surgery with AI-assisted navigation. Improving diagnostic accuracy necessitates utilizing public databases of moving images and developing robust programs.

Additionally, this review discussed autonomous surgical robots, with the STAR system being prominently featured. Advancements in automatic suturing and anastomosis systems demonstrate ongoing innovation. Future endeavors should extend to developing applications for other surgical techniques like incisions. In the interim, the focus remains on developing semi-automatic systems capable of executing simple tasks, with a standby human surgeon available to intervene in emergencies.

To realize the ultimate goal of an autonomous surgical robot, integration of the navigation system with the surgical robot is imperative. Specifically, the development of a deep learning model capable of providing feedback from the navigation system to the surgical technique is crucial for achieving this objective.

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