

Autonomous Camera Movement for Robotic-Assisted Surgery: A Survey

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Abstract— *In the past decade, Robotic-Assisted Surgery (RAS) has become a widely accepted technique as an alternative to traditional open surgery procedures. The best robotic assistant system should combine both human and robot capabilities under the human control. As a matter of fact robot should collaborate with surgeons in a natural and autonomous way, thus requiring less of the surgeons' attention. In this survey, we provide a comprehensive and structured review of the robotic-assisted surgery and autonomous camera movement for RAS operation. We also discuss several topics, including but not limited to task and gesture recognition, that are closely related to robotic-assisted surgery automation and illustrate several successful applications in various real-world application domains. We hope that this paper will provide a more thorough understanding of the recent advances in camera automation in RSA and offer some future research directions.*

Keywords— *Robotic-assisted surgery, autonomous, camera movement, task and gesture recognition.*

I. INTRODUCTION

The operating room is a main unit in a hospital where surgical operations are performed. It is a challenging work environment that requires intense cooperation and coordination between a wide range of people and departments [1]. Surgery is continuously subject to technological and medical innovations, illustrated by the accelerated development and introduction of new imaging technologies, advanced surgical tools, navigation and patient monitoring systems [2]. The purpose of these advances is to improve patient treatment while they transform complicity to daily routine [3]. The ultimate goal of RMIS is to program the surgical robot to perform certain difficult or complex surgery in an autonomous manner. However, there is no technical roadmap to a fully autonomous surgical system at the present time [4], [5]. Surgical procedures are commonly categorized by urgency, type of procedure, body system involved, special instrumentation and degree of invasiveness. At a low degree of invasiveness we have Minimally Invasive Surgery (MIS), which involves a small outer incision to insert miniaturized instruments and remote control manipulation of instruments with indirect observation of

the surgical field through a camera (e.g. an endoscope or laparoscope), and is carried out through the skin or through a body cavity or anatomical opening. In contrast, an open surgical procedure or laparotomy requires a large incision to access the area of interest. In MIS surgeries, instead of making incisions, or straight-line cuts on the body, small cuts are made through with the surgical instruments. This minimizes both the bleeding that the patient undergoes and the scarring that occurs afterwards. By use of MIS, a patient may require only a small bandage on the incision, rather than multiple stitches or staples to close a large incision. These usually results in less infection, a quicker recovery time and shorter hospital stays, or allow outpatient treatment [4].

In the age of technology and introducing robots which has their influence all over our life, surgical area is not an exception. Minimally invasive surgery can be done either manually or using a robotic system. Robotic surgery, computer-assisted surgery, and robotically-assisted surgery are terms for technological developments that use robotic systems to aid in surgical procedures. Minimally invasive robotic surgery provides additional advantages over conventional laparoscopic surgery for surgical operations, including an increase in dexterity [5]–[7] and precision [8].

Current RAS systems operate in a master-slave mode, relying exclusively on direct surgeon input [8]. For example, camera controlling in current RAS platforms is an additional task under direct control of the surgeon. In the current FDA-approved system, da Vinci surgical platform (Intuitive Surgical, Sunnyvale, CA, USA) [12], many interface parameters are set once and remain at the same level throughout the operation while different surgical tasks and motions may require different camera behaviors [13]. In robotic assisted surgery, instead of directly moving the instruments, the surgeon uses one of two methods to control the instruments; either a direct tele-manipulator or through computer control [9]. A tele-manipulator is a remote manipulator that allows the surgeon to perform the normal movements associated with the surgery while the robotic arms carry out those movements using end-effectors and manipulators to perform the actual surgery on the patient. In computer controlled systems the surgeon uses a computer to control

the robotic arms and its end-effectors, though these systems can also still use tele-manipulator for their input. One advantage of using the computerized method is that the surgeon does not have to be physically present.

One form of robot used is the remote control of robotic functions referred to as teleoperated robots. Teleoperated robots are controlled remotely by a human being and the remote control signals can be sent through a wire, a local wireless system, over the Internet or by satellite. Teleoperated robots are probably the most common type of medical robot today. These robots are typically controlled by a surgeon or doctor and allow him to perform various tasks and treatments that he would not normally be able to do.

Some advanced systems, not only have internal cameras, but can utilize more scanning technologies like MRI to allow the surgeon to get a real-time view of exactly where in the body the instruments are. This allows the surgeon to have a high level of control over exactly where he/she is directing the instruments. Some examples of surgical robots include the Neuromate stereotactic robot (Renishaw Inc.) for assisting in neurological surgeries, the da Vinci (Intuitive Surgical Inc., CA, USA) and the Zeus robotic surgical system (computer Motion Inc., Goleta, CA, USA). As an example the da Vinci Surgical System introduced in 1999 is becoming a standard in the field of minimally invasive surgery. Some advantages of this system are: better visualization, improved control and reduction in surgeon fatigue [10]. Surgical robotic enables the surgeon to operate in a tele-operation mode with or without force feedback using a master/slave system configuration [11]. In this mode of operation, visualization is obtained from either an external camera or an endoscopic camera.

Task analysis is the analysis of how a task is accomplished, including a detailed description of both manual and mental activities. Task analysis emerged from research in applied behavior analysis and still has considerable research in that area [12]. The importance of using a standard task analysis method is that it provides a reproducible framework for breaking down a process following a structured technique. This enables developing a shared understanding or framework for a task, and communicates analysis results in a reproducible and widely understood manner in the industrial engineering and ergonomics communities.



Fig. 1: Illustration of robotic surgery platform

From a task analysis, a vocabulary can be drawn to describe an entire process, ensuring that all involved personnel are employing the same vocabulary and interpretation of each task and subtask definitions. Task analysis provides a representation of the operations that are required to accomplish a goal. This is especially critical when a designer aims to change or enhance a procedure, product, or system. Without a thorough mapping of an objective and its subtasks, it can be difficult to anticipate the influences or effects that a change may have on a system [12], [13]. It is, however, quite clear that to develop any automatic control system, a more detailed comprehension of the surgical procedures is needed [14].

II. LITREATURE REVIEW

As the camera positioning problem is highly multi-disciplinary, we decided to present the different related areas. We first briefly present literature addressing gesture recognition and segmentation, with a focus on minimally invasive surgery and surgeon gesture classification based on task analysis. We then focus on camera positioning and zooming level during laparoscopic surgery.

2.1 Surgical task recognition

Recognition of surgical procedure from different granularity level become one of the recent interest of researchers [14]. The most focus is on phase recognitions and different paper use different methods to recognize surgery phases [14]. Forestier et. al. [15] used dynamic time warping to classify surgical process. Lange et. al. [16] did phase recognition in an operating room using sensor technology. Workflow and activity modeling have been worked [17] in order to monitor surgical procedures. With all these systems, information gathered incorporates end-effector data to some extent. Whether information is gathered from magnetic motion tracking of a hand holding manual MIS instruments, or the end-effector

trajectories are encoded from the da Vinci Application Programming Interface, all data is collect from end-effector. Although there are several advantages using end-effector information but there are some limitation as well. The good point is that it helps reduce the effects of other factors including fatigue that can result in added hand tremors, effects of motion scales, etc. However, pervious work successfully demonstrated that a system could be used to identify surgical gestures with great accuracy; a lack of variability presented some question as to the robustness of the system. The limited number of gestures identified in their study does not accommodate for noise that may stem from a mistake or surgery deviations. If, for instance, a surgeon makes a poor stitch and must correct it by undoing it, the classification system would certainly misclassify the task for lack of correct options to choose from. On the other hand, the major weakness of the approaches discussed above is not relying on a structured decomposition of the task. To make a classification system more robust, Golenberg et al. [12] developed Hierarchical Task Analysis of a robotically assisted four-throw suturing task and they presents a classification system that automatically and accurately identifies 24 surgeon subtasks from library with accuracy of 94.56% which is based on rudimentary hand movements. The importance of using a structured task analysis method is that it enables us to have a reproducible framework which provides consistency and can be generalized to be applied in other platforms. Using a structured approach also makes data more acceptable and interpretable since the creation of a gesture breakdown would follow guidelines and rules. Additionally, a thorough task analysis could help ensure that a robust system could be less brittle to less common gestures occurring during surgery deviations, errors, and error recovery.

In one hand, the feasibility of current robotic surgery systems to record quantitative motion and video data motivates the development of descriptive mathematical models to recognize and analyze surgical tasks. On the other hand, recent advances in machine learning research for uncovering concealed patterns in huge data sets, like kinematic and video data, offer a possibility to better understand surgical procedures from a system point of view. Therefore, distance-based time series classification framework for task recognition has been developed [18].

2.2 Surgical gesture recognition and segmentation

Gesture recognition is a topic in computer science and language technology with the goal of interpreting human gestures using mathematical algorithms. Human gesture recognition is a large research domain that has been studied widely in the last decades. The trend is highly motivated by the wide variety of applications concerned

with understanding human gesture such as human-machine interaction and medical monitoring. Gesture recognition enables humans to communicate with the machine and interact naturally without any mechanical devices. Several methods have been used for gesture recognition such as template-matching [19], dictionary lookup [20], statistical matching [21], [22], linguistic matching [23], neural network [24], and ad hoc methods. The key problem in gesture recognition is how to make gestures understood by computers for example how we can make computer understand hand or head gesture. For the hand gesture recognition, the approaches present can be mainly divided into “Glove-Based” and “Vision-Based” approaches. The gloved based methods use sensor devices to capture hand and finger motions into multi-parametric data. However, the devices are quite expensive and cumbersome to the users [25]. In contrast, the vision-based methods require only a camera [26] in order to realize natural interaction between humans and computers and there is no need for any extra devices. Many studies have be done on the area of vision-based hand gesture recognition for human computer interaction, consolidating the various available approaches, pointing out their general advantages and disadvantages [27], [28]. In the area of surgery, significant research has been conducted over the past ten years for gesture recognition of surgeon. They have been assessed in many studies by either tracking the surgeon’s body motion in the operation room [29] or hand motion while performing a specific surgical task [30], [31] and [11]. The Imperial College Surgical Assessment Device (ICSAD) system tracks the surgeon’s hand motions during surgery using electromagnetic markers [31]. In related work, [32] focuses on the analysis of kinematic parameters of motion including translation and rotation of both the tool and camera.

Several research groups have examined movement characteristics directly, seeking low-level signal processing features that can be used to automatically differentiate surgeons into different skill levels [33]. Lin et al. [30] used a neural network modeling approach to classify signals recorded on the da Vinci surgical robot into eight surgeon gestures which shows below:

- 1) Reach for needle
- 2) Position needle
- 3) Insert and push needle through tissue
- 4) Move to middle with needle (left hand)
- 5) Move to middle with needle (right hand)
- 6) Pull suture with left hand
- 7) Pull suture with right hand
- 8) Orient needle with both hands

The extension of [30] is Reiley et al.’s [34] work that also used the da Vinci, but with a larger participant pool. They

used eleven surgical gestures, adding three gestures to Lin's vocabulary; right hand assisting left while pulling suture, loosen up more suture, and end trial. These additional gestures were added by necessity from their surgery observations.

In manual minimally invasive surgery, the signals are often recorded through magnetic trackers or color markers. Cristancho [35] used a Polhemus 3SPACE Fastrak 6-dof electromagnetic system to track conventional manual laparoscopic tools and used Principal Components Analysis (PCA) to determine the main contributors to overall task variability. Richards et. al. [36] applied force and torque sensors to manual laparoscopic tools and found a significant difference in the force and torque signatures of basic movements between novice and expert surgeons. With the advent of new technology for capturing data, more sophisticated machine learning method has been developed [37], [38].

2.3 Camera movement and positioning

Visualization of the surgical field is vital to have a successful operation in both open and laparoscopic operations. Whereas during open procedures surgeons control visualization directly by their own eye movements and tissue manipulation, visualization during laparoscopy relies heavily on an assistant who navigate the laparoscope. Among a number of differences between open and laparoscopic surgery, such as fulcrum effect or tactile feedback, there is a disturbance between surgeon's hands and eyes by interposition of a camera, which moves independently of the surgeon.

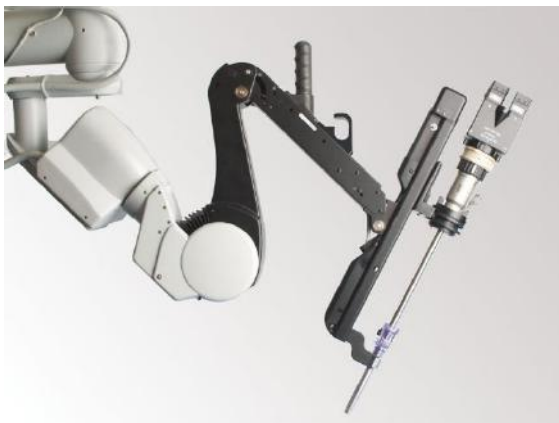


Fig. 2: Camera arm of robotic surgery device

The camera is sometimes held by a medical student or junior resident, who may be unfamiliar with the surgical procedure, may stand in an uncomfortable position, or become fatigued or distracted. This results in the camera rotating away from the horizon and/or inadvertent drifting away from the surgical field with increased rates of surgical errors [39]. In fact, surgical errors leading to injuries mostly because of misperception, rather than lack

of knowledge or judgment [40]. Mechanical camera holders, passive or robotic, may provide surgeons with a more stable image and enable them to control their own view direction [41].

To improve the current mode of laparoscopic surgery, many mechanical scope positioning systems have been proposed [42]. The general idea is to have a robot holding the scope and responding to the positioning commands given by the surgeon through a speech interface system, a hand-held controller or a foot pedal, or other interface mechanisms. In this regard 'choreographed' scope maneuvering capability in laparoscopy was developed with active vision guidance [43].

To free the surgeon from the task of controlling the view and to automatically offer an optimal and stable view during laparoscopic surgery, several automatic camera positioning systems have been devised. These systems visually extract the shape and/or position of the surgical instrument from the laparoscopic images in real time, and automatically manipulate the laparoscope to center the tip of the instrument in the displayed image. In a laparoscopic image, these systems are based on the simple idea that the surgeon's region of interest is corresponding to the projected position of the surgical tool end part. Besides centering on the most interesting area, there is an additional and important factor that defines a good image of the surgical scene that corresponds to the depth of insertion of the laparoscope along its longitudinal axis.

The pioneering studies of fully automatic camera positioning systems defined the zooming ratio as a "uniform" function of the estimated distance between the tip of the tool and the laparoscope [44] or the area ratio between the visible tool and the whole image [45]. Although this method is entirely possible to remove surgeon task controlling the camera but it does not provide specific view that the surgeon is considering, due to the fact that the ratio of camera zooming is widely different during operative. The best zooming ratio depends on both the surgical procedure/phase and the habits/preferences of the operating surgeon. For this reason, most of the instrument tracking systems recently developed [46] and [47] have abandoned the idea of systematic control of zooming parameters; instead, the surgeon is required to define the parameters preoperatively or adjust them intra-operatively through conventional human-machine interfaces, which again means an extra control burden for the surgeon.

To overcome this problem, [48] first investigated how the camera assistant decides the zooming ratio of laparoscopic images by fully analyzing the positional relationship between the laparoscope and the surgical instrument during laparoscopic surgery. They extracted the zooming behavior and implemented it in a robotic

laparoscope positioner that has been developed. As a result, the zooming behavior of their robotic system became very similar to that of the human camera assistant. It was found that the proposed zooming motion in the robotic system can be suitable for fast and compact operations during laparoscopic surgery.

As previous researches show, having an accurate view for surgeon during laparoscopic surgery is very important but unfortunately there is less attention to this fact. Although compare to manually control of camera, robotic system improve the quality of picture during surgery in terms of positioning and zooming but deep study should have be done in this area.

III. FUTURE DIRECTIONS

As described in pervious section, the use of laparoscopic surgery has increased rapidly during the past two decades due to the fact that it is much less traumatic than regular surgery, which result in less postoperative pain and shorter recovery time after surgery. During laparoscopic surgery, endoscopic instruments are passed through small incisions on the abdominal wall, to reach the surgical site within the patient's abdomen. Special camera is attached to a long stem laparoscopic lens to provide an inside view of the surgical site and allows the surgeon to explore the intra-abdominal organs and structures.

In conventional laparoscopic surgery, both hands of the surgeon are engaged with surgical instruments, so the laparoscopic camera is handled by an assistant who is responsible for all camera controlling such as holding and maneuvering the laparoscope following surgeon needs. It is obvious that this cooperation between camera controller and surgeon requires a high degree of coordination, which is not as simple we might think to achieve and maintain during the entire procedure due to the long duration of surgery. There have been efforts to facilitate camera manipulation tasks during laparoscopic surgery procedures by employing robotic systems. The major impact of these robots in laparoscopic surgery is to reduce the need for assistive staff, to provide a larger space for surgeon maneuvers and also to provide direct control over the laparoscopic camera with high stability and geometrical accuracy and no fatigue and inattention. The surgeon controls the motion of the endoscope using a human-machine interface, e.g. a joystick, foot pedal, voice or tracking surgeon head movements.

With all these development in the laparoscopic surgery, it is still an open area for research to find a way to predict surgeon view and camera positioning and zooming ratio during surgery and in order to do so we should have generalized identification of surgeon gesture using task analysis. The gesture classes we are focusing on are reach for needle, position needle, insert and push needle

through tissue, move to middle with needle both hands, pull suture with right or left hand and orient needle with both hands. One important direction for this research are is developing a quantitative model can predict camera positioning and zooming ratio based on surgeon gestures validated through task analysis methods. Answering this question requires an exhaustive knowledge within multidisciplinary fields including knowledge about the surgery tasks, gesture recognition and camera positioning and zooming ratio. So in order to find an optimal camera mode for fundamentals of laparoscopic surgery (FLS) different methods are going to use that discuss in next chapter.

As described before, in conventional laparoscopic surgery, a human assistant controls the laparoscopic image by directing the laparoscope on the operative field, following the instructions of the surgeon. This task requires active communication between the surgeon and the assistant, which result in arising confusion or physical space conflicts. Because the surgeon must focus on directing the assistant, he or she is distracted from actual operation. Furthermore, human camera control may result in not having optimal image due to tremor, off-center drift or the loss of horizontal orientation and therefore frequent correction is required. Moreover, in almost all laparoscopic surgery, images are highly magnified so slight hand trembling induces annoying jitter in the video display. Consequently, a waste of operator effort and a risk to the patient both result.

On the other hand, it is possible to give the surgeon direct control of his/her visual feedback, eliminating the assistant control. The procedure can thus be performed faster and with greater ease. However, giving the surgeon direct control has the undesired side effect that the surgeon is completely being distracted to maneuver the scope. Using robotic camera assistant in laparoscopic surgery has proven to be beneficial in this case. This mode of operation improves the visual feedback and camera control to the surgeon.

Altogether, current positioners rely completely on the surgeon's interactive commands, even within robotic assistants, and lack the intelligence to automate the camera control. The question arise here is "Can we anticipate the surgeon's viewing need to position the scope without the surgeon's intervention using task analysis method?" To address this question, we should explore two different questions:

1. How can we predict next surgeon gesture having previous gesture using dynamic real time data and task analysis method?
2. How can camera position and zooming level of a surgery be recognized using task analysis method?

To answer both questions, first we should have a deep knowledge about tasks and sub-tasks during surgery. For this purpose first we limit ourselves to suturing task, one of the important and complex surgical tasks, and then try to generalize our model to other tasks such as cutting or placement and securing of ligating loop. Also another advantage of choosing suturing procedure is that we are able to anticipate camera exact position and zooming level because the scope aiming and movements are repetitive and follow a fixed pattern and it is zooming in when the surgeon is tying a knot and zooming out when the surgeon is pulling on the suture. Though, the general question above will change to this specific question: "How can we find the exact time when the surgeon is tying a knot to zooming in or pulling on the suture to zoom out?" Although we could have an overall anticipation based on the suturing structural procedure but a precise prediction of next step camera positioning and zooming is desired during the dynamic atmosphere of surgery procedure that may vary from surgeon to surgeon. In current laparoscopic surgery, the vision of the operating surgeon usually depends on the camera assistant responsible for guiding the laparoscope. The assistant holds the laparoscope for the surgeon and positions the scope according to the surgeon's instructions. Commands are often interpreted and it causes this method become frustrating and inefficient for the surgeon. Also, the scope is sometimes aimed incorrectly and vibrates or drifts because of the assistant, resulting in suboptimal and unstable view. The robotic technologies, specifically, the development of robotic laparoscope positioning systems is a major step toward solving this problem.

One important difference between robotic-assisted and manual laparoscopic surgery is that the control of the endoscope transfers to the surgeon. In manual laparoscopic surgery, another surgeon, resident or staff person is responsible for this role. Although the control of the camera eliminates the need for other assistant during procedure but giving the control to the surgeon is adding an additional task to an already overloaded surgeon. For this reason, allowing a robot to automatically control the zoom based on the surgeon's task has a great opportunity to contribute to a surgeon's performance. Ellis et al. [49], [50] demonstrated that the zoom level had a significant effect on surgeon performance. Removing the task of camera control from the surgeon would relieve the surgeon of a task and ensure quick and responsive camera control.

IV. CONCLUSION

In this paper, we report the recent development on the research of camera positioning in robotic assisted surgery with focus on various computational analytic techniques.

As the camera positioning problem is highly multi-disciplinary, we presented the different related areas such as addressing gesture recognition and segmentation, with a focus on robotic assisted surgery and surgeon gesture classification based on task analysis. We then focus on camera positioning and zooming level during laparoscopic surgery. Various method on algorithms on this are surveyed in this paper. Overall, autonomous camera movement and positioning for robotic assisted surgery is still in its infancy. It involves the cooperation of many disciplines. In order to understand this better, not only for machines, but also for humans, substantial research efforts in computer vision, machine learning and psycholinguistics will be needed.

REFERENCES

- [1] M. J. Fard, "Computational Modeling Approaches for Task Analysis in Robotic-Assisted Surgery," Wayne State University, 2016.
- [2] A. R. Lanfranco, A. E. Castellanos, J. P. Desai, and W. C. Meyers, "Robotic Surgery," *Ann. Surg.*, vol. 239, no. 1, pp. 14–21, 2004.
- [3] A. Cuschieri, "Whither minimal access surgery: tribulations and expectations.," *Am. J. Surg.*, vol. 169, no. 1, pp. 9–19, Jan. 1995.
- [4] M. J. Fard, S. Ameri, and R. D. Ellis, "Toward Personalized Training and Skill Assessment in Robotic Minimally Invasive Surgery," in *Lecture Notes in Engineering and Computer Science: Proceedings of The World Congress on Engineering and Computer Science 2016*, 2016.
- [5] K. Moorthy, Y. Munz, A. Dosis, J. Hernandez, S. Martin, F. Bello, T. Rockall, and A. Darzi, "Dexterity enhancement with robotic surgery," *Surg. Endosc.*, vol. 18, no. 5, pp. 790–5, May 2004.
- [6] S. Ku, S. E. Salcudeai, and B. Columbia, "Dexterity Enhancement in Microsurgery using a Motion-Scaling System and Microgripper," pp. 77–82, 1995.
- [7] S. Ameri, M. J. Fard, R. B. Chinnam, and C. K. Reddy, "Survival Analysis based Framework for Early Prediction of Student Dropouts," in *Proceedings of the 25th ACM International on Conference on Information and Knowledge Management - CIKM '16*, 2016, pp. 903–912.
- [8] G. F. Dakin and M. Gagner, "Comparison of laparoscopic skills performance between standard instruments and two surgical robotic systems," *Surg. Endosc.*, vol. 17, no. 4, pp. 574–9, Apr. 2003.
- [9] A. K. Pandya, L. A. Reisner, B. W. King, N. Lucas, A. M. Composto, M. D. Klein, and R. D. Ellis, "A Review of Camera Viewpoint Automation in Robotic and Laparoscopic Surgery," *Robotics*, vol. 3, pp. 310–329, 2014.

- [10] L. Tao, L. Zappella, G. D. Hager, and R. Vidal, "Surgical gesture segmentation and recognition," *Lect. notes Comput. Sci.*, pp. 339–346, 2013.
- [11] J. Rosen, J. D. Brown, L. Chang, M. N. Sinanan, and B. Hannaford, "Generalized approach for modeling minimally invasive surgery as a stochastic process using a discrete Markov model," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 3, pp. 399–413, Mar. 2006.
- [12] L. P. Golenberg, "Task Analysis , Modeling , And Automatic Identification Of Elemental Tasks In Robot- Assisted Laparoscopic Surgery," 2010.
- [13] M. J. Fard, S. Ameri, R. Darin Ellis, R. B. Chinnam, A. K. Pandya, and M. D. Klein, "Automated robot-assisted surgical skill evaluation: Predictive analytics approach," *Int. J. Med. Robot. Comput. Assist. Surg.*, p. e1850, Jun. 2017.
- [14] F. Lalys and P. Jannin, "Surgical process modelling: a review.," *Int. J. Comput. Assist. Radiol. Surg.*, vol. 9, no. 3, pp. 495–511, 2014.
- [15] G. Forestier, F. Lalys, L. Riffaud, B. Trelhu, and P. Jannin, "Classification of surgical processes using dynamic time warping," *J. Biomed. Inform.*, vol. 45, no. 2, pp. 255–64, Apr. 2012.
- [16] J. E. Bardram, A. Doryab, R. M. Jensen, P. M. Lange, K. L. G. Nielsen, and S. T. Petersen, "Phase recognition during surgical procedures using embedded and body-worn sensors," *2011 IEEE Int. Conf. Pervasive Comput. Commun.*, pp. 45–53, Mar. 2011.
- [17] N. Padoy, "Workflow and Activity Modeling for Monitoring Surgical Procedures," Technical University of Munich, 2010.
- [18] M. J. Fard, A. K. Pandya, R. B. Chinnam, M. D. Klein, and R. D. Ellis, "Distance-based time series classification approach for task recognition with application in surgical robot autonomy," *International Journal of Medical Robotics and Computer Assisted Surgery*, 2016.
- [19] J. S. Lopscomb, "A trainable gesture recognizer," *Pattern Recognit.*, vol. 24, no. 9, pp. 895–907, 1991.
- [20] W. M. Newman and R. F. Sproull, *Principles of Interactive Computer Graphics*. McGraw-Hill, 1974.
- [21] D. H. Rubine, "The Automatic Recognition of Gestures," Carnegie Mellon University, 1991.
- [22] M. J. Fard, P. Wang, S. Chawla, and C. K. Reddy, "A Bayesian Perspective on Early Stage Event Prediction in Longitudinal Data," *IEEE Trans. Knowl. Data Eng.*, vol. 28, no. 12, pp. 3126–3139, Dec. 2016.
- [23] K. S. Fu, "Syntactic recognition in character recognition," *Math. Sci. Eng.*, vol. 112, pp. 6–7, 1974.
- [24] G. E. H. S. Sidney Fels, "Glove-talk: a neural network interface between a data- glove and a speech synthesizer," *IEEE Trans. neural networks*, vol. 3, no. 6, pp. 2–8, 1992.
- [25] A. Mulder, "Hand Gestures for HCI," *Tech. Rep.*, no. February, 1996.
- [26] R. Gopalan and B. Dariush, "Toward a vision based hand gesture interface for robotic grasping," *2009 IEEE/RSJ Int. Conf. Intell. Robot. Syst.*, pp. 1452–1459, Oct. 2009.
- [27] P. Garg, N. Aggarwal, and S. Sofat, "Vision Based Hand Gesture Recognition," *World Acad. Sci. Eng. Technol.*, pp. 972–977, 2009.
- [28] Y. Wu and T. S. Huang, "Hand modeling analysis and recognition for vision-based human computer interaction," *IEEE Signal Process. Mag.*, vol. 18, no. 3, pp. 51–60, 2001.
- [29] C. Lenz, A. Sotzek, R. Thorsten, M. Huber, and S. Glasauer, "Human Workflow Analysis using 3D Occupancy Grid Hand Tracking in a Human-Robot Collaboration Scenario," pp. 3375–3380, 2011.
- [30] H. C. Lin, I. Shafran, D. Yuh, and G. D. Hager, "Towards automatic skill evaluation: detection and segmentation of robot-assisted surgical motions.," *Comput. Aided Surg.*, vol. 11, no. 5, pp. 220–230, 2006.
- [31] Y. Munz, A. M. Almoudaris, K. Moorthy, A. Dosis, A. D. Liddle, and A. W. Darzi, "Curriculum-based solo virtual reality training for laparoscopic intracorporeal knot tying: objective assessment of the transfer of skill from virtual reality to reality," *Am. J. Surg.*, vol. 193, no. 6, pp. 774–83, Jun. 2007.
- [32] N. Ahmidi, G. D. Hager, L. Ishii, G. Fichtinger, G. L. Gallia, and M. Ishii, "Surgical gesture classification from eye tracking and tool motion in Minimally Invasive Surgery," *Lect. notes Comput. Sci.*, vol. 63, no. 63, pp. 295–302, 2010.
- [33] M. J. Fard, S. Ameri, R. B. Chinnam, A. K. Pandya, M. D. Klein, and R. D. Ellis, "Machine Learning Approach for Skill Evaluation in Robotic-Assisted Surgery," in *Lecture Notes in Engineering and Computer Science: Proceedings of The World Congress on Engineering and Computer Science 2016*, 2016.
- [34] C. E. Reiley, H. C. Lin, B. Varadarajan, B. Vagvolgyi, S. Khudanpur, D. D. Yuh, and G. D. Hager, "Automatic recognition of surgical motions using statistical modeling for capturing variability," *Stud. Health Technol. Inform.*, vol. 132, no. 1, pp. 396–401, Jan. 2008.
- [35] S. M. Cristancho, "Quantitative modelling and assessment of surgical motor actions in minimally

- invasive surgery,” Vancouver: The University of British Columbia, 2008.
- [36] C. Richards, J. Rosen, B. Hannaford, C. Pellegrini, and M. Sinanan, “Skills evaluation in minimally invasive surgery using force / torque signatures,” pp. 791–798, 2000.
- [37] C. E. Reiley, H. C. Lin, B. Varadarajan, B. Vagvolgyi, S. Khudanpur, D. D. Yuh, and G. D. Hager, “Automatic recognition of surgical motions using statistical modeling for capturing variability.,” *Stud. Health Technol. Inform.*, vol. 132, no. 1, pp. 396–401, 2008.
- [38] M. J. Fard, S. Ameri, R. B. Chinnam, and R. D. Ellis, “Soft Boundary Approach for Unsupervised Gesture Segmentation in Robotic-Assisted Surgery,” *IEEE Robot. Autom. Lett.*, vol. 2, no. 1, pp. 171–178, Jan. 2017.
- [39] A. G. Gallagher, M. Al-Akash, N. E. Seymour, and R. M. Satava, “An ergonomic analysis of the effects of camera rotation on laparoscopic performance.,” *Surgical endoscopy*, vol. 23, no. 12, pp. 2684–91, Dec-2009.
- [40] L. W. Way, L. Stewart, W. Gantert, K. Liu, C. M. Lee, K. Whang, and J. G. Hunter, “Causes and Prevention of Laparoscopic Bile Duct Injuries,” vol. 237, no. 4, pp. 460–469, 2003.
- [41] J. Jasper, P. Breedveld, and J. Herder, “Camera and instrument holders and their clinical value in minimally invasive surgery,” *Surg Laparosc Endosc Percutan Tech*, vol. 14, pp. 145–152, 2004.
- [42] R. Hurteau, S. Desantis, and E. P. De Montrial, “Laparoscopic Surgery Assisted by a Robotic Cameraman: Concept and Experimental Results,” pp. 2286–2289, 1994.
- [43] Y. F. Wang, D. R. Uecker, and Y. Wang, “A new framework for vision-enabled and robotically assisted minimally invasive surgery,” *Comput. Med. Imaging Graph.*, vol. 22, no. 6, pp. 429–37, 1999.
- [44] G. Wei and G. Hirzinger, “Real-Time Visual Servoing for Laparoscopic Surgery,” *Eng. Med. Biol. Mag. IEEE*, vol. 16, no. 1, pp. 40–45, 1997.
- [45] A. Casals and J. Amat, “Automatic Guidance of an Assistant Robot in Laparoscopic Surgery,” no. April, pp. 895–900, 1996.
- [46] S. Ko and D. Kwon, “A surgical knowledge based interaction method for a laparoscopic assistant robot,” *RO-MAN 2004. 13th IEEE Int. Work. Robot Hum. Interact. Commun. (IEEE Cat. No.04TH8759)*, pp. 313–318, 2004.
- [47] S. Yamaguchi, A. Nishikawa, J. Shimada, K. Itoh, and F. Miyazaki, “Real-time image overlay system for endoscopic surgery using direct calibration of endoscopic camera,” *Int. Congr. Ser.*, vol. 1281, pp. 756–761, May 2005.
- [48] A. Nishikawa, H. Nakagoe, K. Taniguchi, and Y. Yamada, “How Does the Camera Assistant Decide the Zooming Ratio of Laparoscopic Images ?,” pp. 611–618, 2008.
- [49] R. D. Ellis, a. Cao, a. Pandya, a. Composto, M. Chacko, M. Klein, and G. Auner, “Optimizing the Surgeon-Robot Interface: The Effect of Control-Display Gain and Zoom Level on Movement Time,” *Proc. Hum. Factors Ergon. Soc. Annu. Meet.*, vol. 48, no. 15, pp. 1713–1717, Sep. 2004.
- [50] R. D. Ellis, a. Cao, a. Pandya, a. Composto, M. D. Klein, and G. Auner, “Minimizing Movement Time in Surgical Telerobotic Tasks,” *Proc. Hum. Factors Ergon. Soc. Annu. Meet.*, vol. 49, no. 11, pp. 1099–1103, Sep. 2005.