

# Surgical Subtask Automation—Soft Tissue Retraction

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**Abstract**—Robot-assisted surgery is becoming standard-of-care in minimally invasive surgery. Given the intense development in this area, many believe that the next big step is surgical subtask automation, the partial automation of certain elements of the procedure. Autonomous execution at lower task levels has the potential to safely improve one element of a surgical process. Automation by artificial intelligence may significantly improve surgery with better accuracy and targeting, that can shorten the recovering time of the patient. Furthermore, partial automation can also help surgeons efficiently by reducing the fatigue in the case of time-consuming operations. In this paper, we present the automation of *soft tissue retraction*, an often recurring subtask of surgical interventions. Soft tissue retraction plays an important role in laparoscopic cholecystectomy, e.g., during the exploration of the Calot triangle, automatic retraction would streamline the procedure. The presented method only relies on a stereo camera image feed, and therefore does not put additional overhead on the already crowded operating room. We developed and tested multiple control methods for soft tissue retraction built on each other: a simple proportional control for reference, one using Hidden Markov Models for state estimation, and one employing fuzzy logic. Our method was tested comparatively with all three controllers in a simplified phantom environment.

## I. INTRODUCTION

In the last decades, Minimally Invasive Surgery (MIS) had a significant influence on medicine. Unlike traditional open surgery, MIS uses so-called laparoscopic tools inserted through small incisions, while the area of operation is observed by an endoscopic camera. Nowadays a vast number of interventions can be performed minimal invasively, that benefits both the patients and the hospitals—MIS usually means shortened stay in hospital, lower risk of complications and smaller trauma [1].

The wide spread of MIS poses new challenges to the surgeons, such as cumbersome positions and limited range of motion. Teleoperated laparoscopic surgical robots—like the da Vinci Surgical System (Intuitive Surgical Inc., Sunnyvale, CA [2])—appeared to ease these difficulties. Despite the obvious advantages, the workflow of surgical procedures performed by teleoperated systems tend to contain a number of time-consuming and monotonous subtasks. Automating such subtasks might reduce the cognitive load on the surgeon, and allow them to better focus on the more critical operations [3][4][5][6].

Soft tissue retraction is an often recurring subtask in the surgical workflow. Retraction means the delicate manipulation

of an organ or tissue in such a way that it makes possible the execution of another subtask. The aim of retraction can either be maintaining tension (e.g. for blunt dissection or clipping), or only to give access to the tissue below. This subtask is an important element of many interventions, e.g., can be found in the workflow of laparoscopic cholecystectomy; retraction is used during the dissection of the cystic duct and artery, or during the separation of the gallbladder and the liver [7]. Notably that, this subtask is relatively easy to perform for a human operator, and thus often done by a surgical assistant.

In our previous work, the automation of another surgical subtask—blunt dissection—is shown [8]. Blunt dissection is usually used to separate loosely connected layers of tissue without damaging sensitive anatomical structures like nerves or blood vessels. Therefore, during this subtask no sharp instruments are used, the layers of tissue are separated by gentle opening movements of the instrument’s jaws. In the case of blunt dissection, the retraction of the upper layer is crucial, both to give access to the area of dissection and to create tension between the layers to be separated.

In this paper, an algorithmic solution to soft tissue retraction is presented. Despite that retraction can be performed in many ways, e.g., push or lift without grasping, here we are focus on the one done by grasping and pulling the tissue. Although this is one of the easiest subtask in surgery for a human operator, its autonomous execution presents difficulties. Most of the available surgical robotic systems—including the da Vinci—lack the ability of force sensing due to the size and issues with sterilization of force sensors. For that reason, no force sensors are used in our method; the state (angle and tension) of the retracted tissue is estimated by stereo video stream, which is already available in the operating room.

## II. MATERIALS AND METHODS

### A. Surgical phantom

The solution for autonomous retraction presented in this paper was developed and tested on a simplified soft tissue phantom environment, similar to the one used for blunt dissection [8]. This phantom consists of two harder layers of silicone connected by a softer, destructible silicone layer (Fig. 1).

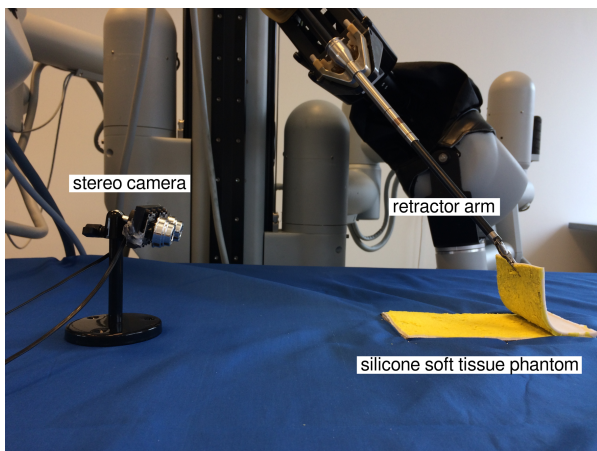


Fig. 1: System setup for autonomous retraction. The stereo camera pair, the tissue phantom and the da Vinci slave arm (controlled by the da Vinci Research Kit).

### B. Da Vinci Research Kit (dVRK)

Our method was implemented on the da Vinci Surgical System, controlled by the da Vinci Research Kit that interfaces the robot to Robot Operating System (ROS) [2][9]. The retraction is performed with a single instrument of the da Vinci, which was registered to the coordinate frame of the stereo camera pair.

### C. Vision system

Since we do not currently have access to the image feed from the built-in endoscopic stereo camera of the da Vinci, a pair of low-cost USB cameras was used as stereo camera pair (Fig. 1). It is worth mentioning that this method can be ported easily onto the da Vinci's imaging system in the future. Our solution relies solely on the stereo camera images, hence it would not require any additional device to be installed in the already crowded operating environment.

The USB cameras were mounted on a stable frame 50 mm from each other. The cameras were used in 640x480 pixel resolution, with fixed focal length. The video stream of the camera pair was obtained through ROS. The stereo camera pair was calibrated by the ROS camera\_calibration package using a 25x25 mm checkerboard pattern [10].

The state of retraction can be estimated using the disparity map of the scene, calculated by the ROS stereo\_image\_proc package using Block Matching (BM) algorithm [11]. The rectified stereo images and the disparity map is read from the ROS topic in Matlab, where all further image processing is done as described below.

## III. ESTIMATING THE STATE OF RETRACTION

The execution of retraction has to start with the grasping of the edge of the tissue to be retracted. The point of grasping is marked with red color to ease testing, although it can also be chosen on the camera image manually by the surgeon. After grasping, the tissue is lifted slightly (20-30 mm) to make the camera able to see in between the layers.

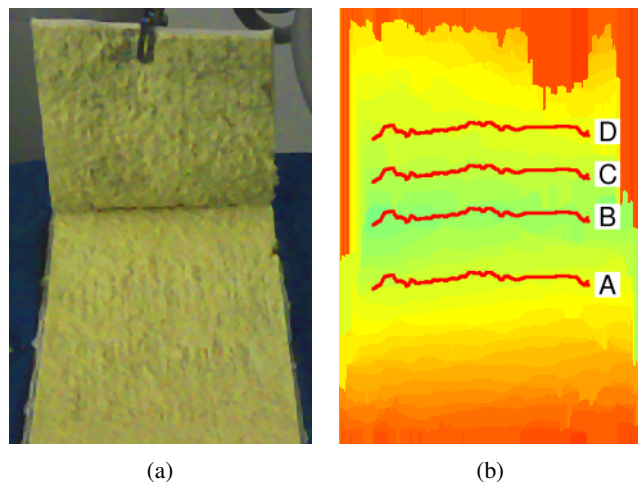


Fig. 2: The camera scene during retraction; (a) the rectified camera image and (b) the disparity map with the detected lines used for state estimation.

Since in the presented method no force sensors to be employed, the position and tension of the retracted tissue were estimated based on stereo vision as follows. First, the Region of Interest (ROI) is calculated by the big cut-offs experienced at the edges of the tissue layers in the disparity map (Fig. 2). Afterwards, the line where the upper and the lower tissue meets is detected on the disparity map; this horizontal line consist of the vertical local minima of the disparity map [8]. Based on that line—marked with *B* in Fig. 2 and 3—three additional lines are determined on the scene by simply translating it vertically: *A*, *C* and *D*.

The state of the retracted tissue is estimated from the 3D position of lines *A*, *B*, *C* and *D*, calculated from the disparity map. The 3D positions are averaged along these lines, resulting four representative points. Finally, the angles  $\beta$  and  $\gamma$  are calculated (Fig. 3). Angles  $\beta$  and  $\gamma$  are used in the estimation of the angle and the tension of the retracted tissue.

The first angle ( $\beta$ ) is used as a direct estimation for opening angle between the two layers of tissue, while the second angle ( $\gamma$ ) is used for an indirect estimation for the tension of the retracted tissue. Although nor the absolute value of tension cannot be calculated from  $\gamma$ , nor a linear relationship can be given between the two values due to the diversity of tissues, these values are closely related; the function between the tension and  $\gamma$  accounted to be monotonic. This angle is determined by the bending of the tissue, increasing to  $180^\circ$  as bending is decreasing, so below  $180^\circ$  in can be used to estimate tension. A disadvantage of this method is possibly that after the tissue is pulled completely flat,  $\gamma$  will be fixed at  $180^\circ$ , and the force of the pull cannot be determined by this angle only.

## IV. RETRACTION CONTROL

The retraction of the tissue is done using one arm of the da Vinci Surgical System, registered to the coordinate frame of the camera. This subtask is executed solely relying on the

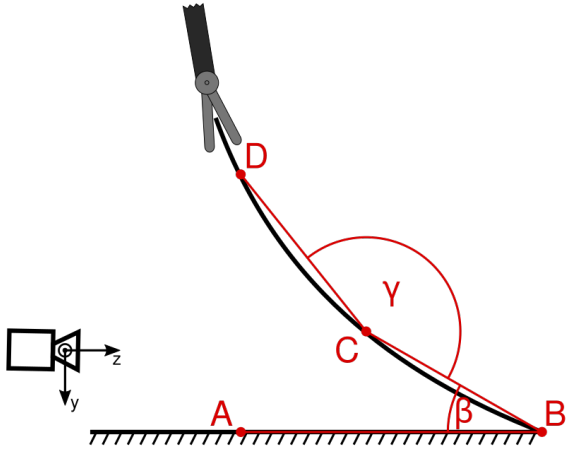


Fig. 3: Schematic image of the estimation method for the angle and tension of the retracted tissue layer. The angle between the two layers of tissue is referred as  $\beta$ ; the angle related to the tension of the retracted tissue is referred as  $\gamma$ .

information gathered from the stereo camera stream, namely  $\beta$  and  $\gamma$ . The retraction is controlled only in two dimensions, along axes  $z$  and  $y$  (Fig. 3). In the following three different methods are presented to control soft tissue retraction.

#### A. Proportional controller

The first control method utilizes a simple proportional controller. Given the current and desired angles,  $\beta_{curr}$ ,  $\gamma_{curr}$ ,  $\beta_{des}$  and  $\gamma_{des}$ , and the length of sections  $BC$  and  $CD$ , the vectors  $\vec{BD}_{curr}$  next to the current, and  $\vec{BD}_{des}$  next to the wanted instrument position can be calculated. The length of sections  $BC$  and  $CD$  is not measured in our case. Since the absolute length is irrelevant, those are assumed to be equal and unity, so 1–1 unit each, and will be scaled using the  $K_p$  parameter of the controller. So, in the current position the vector  $\vec{BD}_{curr}$  can be written as follows:

$$\vec{BD}_{curr} = (-\cos(\beta_{curr}) + \sin(\beta_{curr} - \gamma_{curr} + 180^\circ), -\sin(\beta_{curr}) - \cos(\beta_{curr} - \gamma_{curr} + 180^\circ)) \quad (1)$$

Similarly, in the desired position:

$$\vec{BD}_{des} = (-\cos(\beta_{des}) + \sin(\beta_{des} - \gamma_{des} + 180^\circ), -\sin(\beta_{des}) - \cos(\beta_{des} - \gamma_{des} + 180^\circ)) \quad (2)$$

So the error of the  $D$  point's position can be written as the difference of the above:

$$\vec{e}_D = \vec{BD}_{curr} - \vec{BD}_{des} \quad (3)$$

In the control loop of the retraction this error is used as the feedback of the system, so the position of the instrument in the  $z - y$  plane is controlled as follows:

$$\vec{P}(i+1) = \vec{P}(i) + K_p \vec{e}_D \quad (4)$$

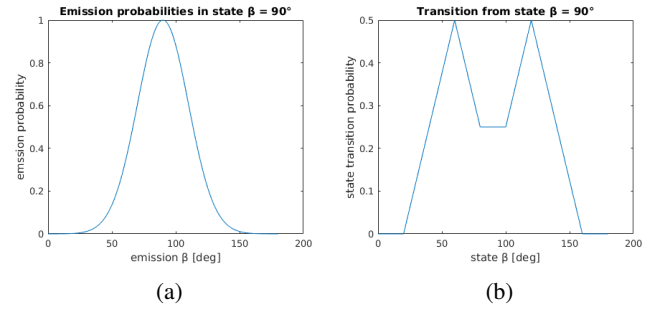


Fig. 4: The emission (a) and transition (b) functions used in the HMM-based method.

#### B. State observation with Hidden Markov Model (HMM)

Since the angle and tension of the retracted tissue is estimated only, the control of these values may be inaccurate. This inaccuracy is reduced using a Hidden Markov Model (HMM) based method. HMMs are modeling a system that possesses a state, that is not observed, its exact value is not known. These systems produces emission values that are related with those inner states, the probability of the emission is considered to be known for each  $\{state, emission\}$  pair. Furthermore the system is also able to transition into another state, the probability of transition between all state pairs is considered to be known, as well [12].

Following these thoughts, HMMs are defined for the values  $\beta$  and  $\gamma$  to enhance the accuracy and reliability of retraction. The real value of these variables are chosen to be the hidden states of the corresponding HMMs, hence exact value of those is not measured; the emitted values of these HMMs are chosen to be the estimations from the computer vision algorithm. The estimated values are assumed to be distributed normally around the real values, so the use of Gaussian emission functions in this approach is a plausible decision. Similarly, the transition probabilities are chosen to be the sum of two triangular distributions with peaks in given distance from the current state, modeling the fact that the next state in the sequence will probably be a bit more, or a bit less than the current due to the manipulation of the tissue (Fig. 4).

Using the defined HMMs and the measured observation sequences of  $\beta$  and  $\gamma$ , the real values of  $\beta$  and  $\gamma$  are can be estimated by the Viterbi algorithm [12]. In this HMM-based method these values are used as the input of the proportional controller mentioned in the subsection above.

#### C. Fuzzy controller

In this paper another method—independent from the previous HMM-based one—is presented to control soft tissue retraction. The control of this movement is based on measurements containing considerably large errors. To reduce the effects of these errors a simple fuzzy controller was also implemented [13]. The inputs and outputs of this controller were chosen to be the same as of the controllers before ( $\{\beta, \gamma\}$  and  $\{z, y\}$ ). The membership functions are chosen to be trapezoidal (Fig. 5). The output surface resulted by the

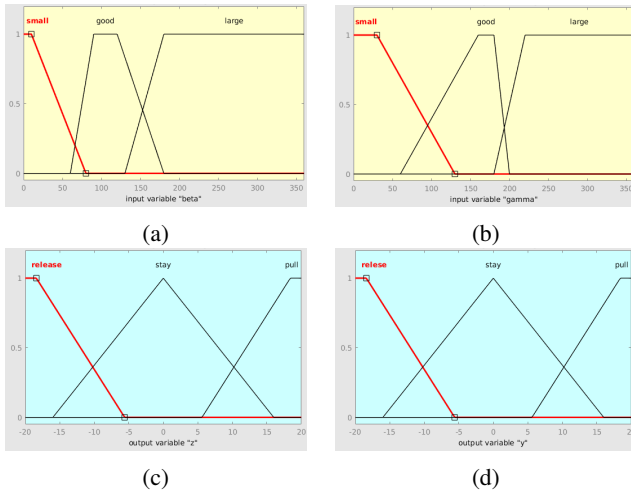


Fig. 5: The membership functions used in the fuzzy controller: (a) and (b) are the membership functions of the input variables  $\beta$  and  $\gamma$ , (c) and (d) are the the membership functions of the output variables  $z$  and  $y$  (the required displacement in axes  $z$  and  $y$ ).

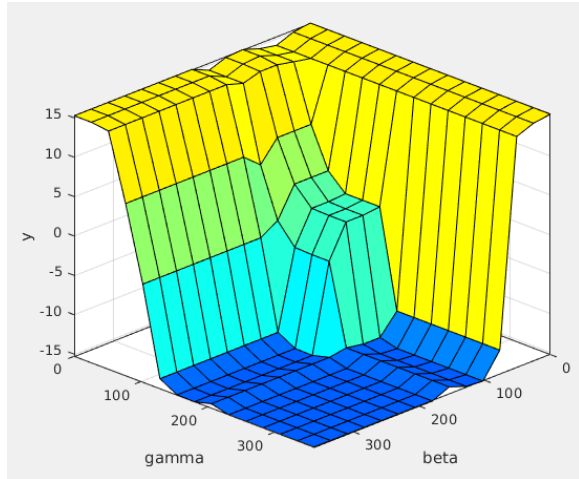


Fig. 6: The output surface of the implemented fuzzy controller for the required displacement in the  $y$  axis of the camera coordinate frame.

rules of the controller can be seen in Fig. 6. The controller was developed and evaluated using the Matlab Fuzzy Logic Toolbox.

## V. RESULTS

The presented methods for soft tissue retraction were tested on the silicone soft tissue phantom described in Subsection II-A. The improvement of the estimated values by HMMs is measured as follows. One of the angles was fixed on the phantom (first  $\gamma$ , secondly  $\beta$ ), while the other was set in a predefined series of angles manually. In the meantime, the estimation from the camera stream was performed in each setting, and according to these estimations the HMM likelihood states were also calculated. The resulting measurements can be seen

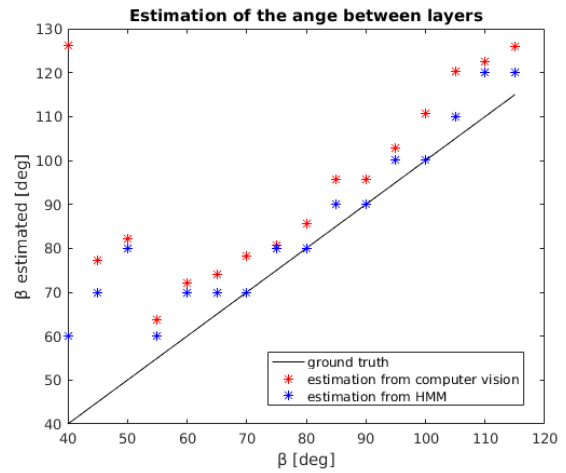


Fig. 7: Testing of the computer vision and HMM-based methods used for the estimation of the angle between the two tissue layers ( $\beta$ ).

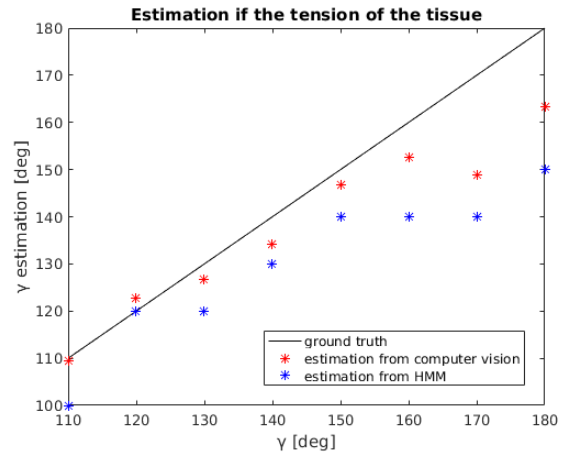


Fig. 8: Testing of the computer vision and HMM-based methods used for the estimation of the angle related to the tension of the retracted tissue ( $\gamma$ ).

in Fig. 7 and 8. The root-mean-square error was calculated from the measured data series, that was decreased by the use of HMM in case of  $\beta$  ( $25.9^\circ$  in the basic method,  $12.0^\circ$  with HMM) and increased in case of  $\gamma$  ( $10.2^\circ$  in the basic method,  $18.0^\circ$  with HMM).

The settling error of the three above-presented methods soft tissue retraction is tested comparatively. A series of 5 experiments were executed with each method, with the target angles  $\beta = 90^\circ$  and  $\gamma = 170^\circ$ . At the end of each session the settled angles were measured manually. The results of these test can be seen in Fig. 9 and 10. Based on these tests, the method utilizes fuzzy logic found to be the best in terms of both precision and accuracy.

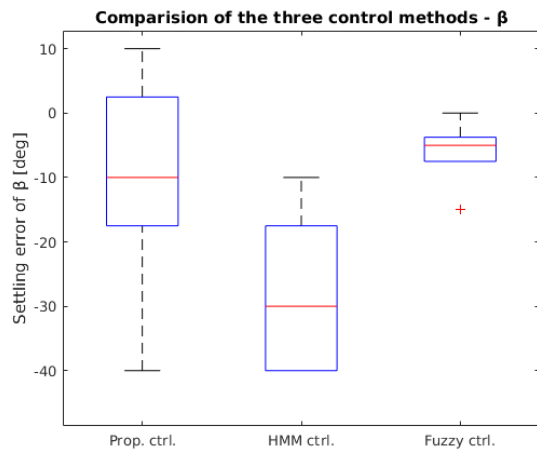


Fig. 9: The measured settling error of the angle of tissue layers ( $\beta$ ) using the presented methods for soft tissue retraction: proportional control, HMM-based proportional control and fuzzy control.

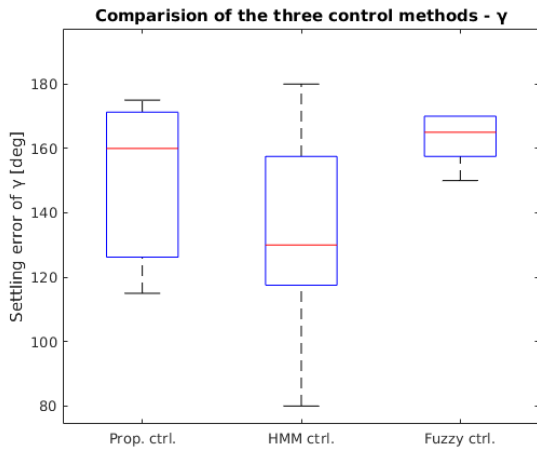


Fig. 10: The measured settling error of the angle  $\gamma$  (related with tension) of the retracted tissue using the presented methods for soft tissue retraction: proportional control, HMM-based proportional control and fuzzy control.

## VI. CONCLUSION AND DISCUSSION

In this paper, the development and testing of different soft computing methods were presented for autonomous soft tissue retraction in robot-assisted minimally invasive surgery. It was shown how the attributes of the retracted tissue can be estimated only using the video stream of a stereo camera, which is already accessible in the operating room, and how this estimation can be enhanced using Hidden Markov Models. These estimations were used to build simple control algorithms to perform the retraction of the tissue autonomously; one using proportional control for reference, one using HMM alongside proportional control, and one based on a simple fuzzy controller. The mentioned methods were all tested in vitro.

In the future, the presented methods can be put through ex vivo experiments as well, where light reflections and a more wide scale of textures and shapes may lead to new difficulties. Furthermore, the presented automated subtask can be used along other autonomous methods, such as our earlier presented blunt dissection algorithm.

## ACKNOWLEDGMENT

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## REFERENCES

- [1] Á. Takács, D. Á. Nagy, I. Rudas, and T. Haidegger, "Origins of Surgical Robotics: From Space to the Operating Room," *Acta Polytechnica Hungarica*, vol. 13, no. 1, pp. 13–30, 2016.
- [2] G. S. Guthart and J. K. J. Salisbury, "The Intuitive™ Telesurgery System: Overview and Application," in *Proc. of IEEE International Conference on Robotics and Automation*, San Francisco, CA, 2000, pp. 618–621.
- [3] T. Osa, K. Harada, N. Sugita, and M. Mitsuishi, "Trajectory planning under different initial conditions for surgical task automation by learning from demonstration," in *Proc. of IEEE International Conference on Robotics and Automation*, May 2014, pp. 6507–6513.
- [4] A. Murali, S. Sen, B. Kehoe, A. Garg, S. McFarland, S. Patil, W. D. Boyd, S. Lim, P. Abbeel, and K. Goldberg, "Learning by observation for surgical subtasks: Multilateral cutting of 3D viscoelastic and 2D Orthotropic Tissue Phantoms," in *Proc. of IEEE International Conference on Robotics and Automation*, May 2015, pp. 1202–1209.
- [5] A. Garg, S. Sen, R. Kapadia, Y. Jen, S. McKinley, L. Miller, and K. Goldberg, "Tumor localization using automated palpation with Gaussian Process Adaptive Sampling," in *Proc. of IEEE International Conference on Automation Science and Engineering*, Aug. 2016, pp. 194–200.
- [6] S. Sen, A. Garg, D. V. Gealy, S. McKinley, Y. Jen, and K. Goldberg, "Automating multi-throw multilateral surgical suturing with a mechanical needle guide and sequential convex optimization," in *Proc. of IEEE International Conference on Robotics and Automation*, May 2016, pp. 4178–4185.
- [7] J. H. Peters, E. C. Ellison, J. T. Innes, J. L. Liss, K. E. Nichols, J. M. Lomano, S. R. Roby, M. E. Front, and L. C. Carey, "Safety and efficacy of laparoscopic cholecystectomy. A prospective analysis of 100 initial patients." *Annals of Surgery*, vol. 213, no. 1, pp. 3–12, Jan. 1991.
- [8] R. Elek, T. D. Nagy, D. Á. Nagy, T. Garamvölgyi, B. Takács, Péter Galambos, József K Tar, Imre J Rudas, and Tamás Haidegger, "Towards surgical subtask automation—blunt dissection," in *Proc. of IEEE 21st International Conference on Intelligent Engineering Systems*, IEEE, Ed. Larnaca: IEEE, 2017, pp. 253–258.
- [9] P. Kazanzides, Z. Chen, A. Deguet, G. S. Fischer, R. H. Taylor, and S. P. DiMaio, "An open-source research kit for the da Vinci® Surgical System," in *Proc. of IEEE International Conference on Robotics and Automation*, May 2014, pp. 6434–6439.
- [10] "Camera\_calibration - ROS Wiki," [http://wiki.ros.org/camera\\_calibration](http://wiki.ros.org/camera_calibration).
- [11] "Stereo\_image\_proc - ROS Wiki," [http://wiki.ros.org/stereo\\_image\\_proc](http://wiki.ros.org/stereo_image_proc).
- [12] L. Rabiner and B. Juang, "An introduction to hidden Markov models," *IEEE ASSP Magazine*, vol. 3, no. 1, pp. 4–16, Jan. 1986.
- [13] L. A. Zadeh, "Fuzzy sets as a basis for a theory of possibility," *Fuzzy Sets and Systems*, vol. 1, no. 1, pp. 3–28, Jan. 1978.