Journal of Research High School

Vol. 2024 (11) 466 – 473
ISSN 2688-3651 [online]

Learning-Based Control of a Soft Robot in Minimally Invasive Surgery

Namya Bhargava[1 *]

[1]Evergreen Valley High School, San Jose, CA, USA
*Corresponding Author: bhargava.namya@gmail.com

Advisor: Dr. Thomas George-Thuruthel, t.thuruthel@ucl.ac.uk

Received June 25, 2023; Revised July 1, 2024; Accepted July 24, 2024

Abstract

Minimally invasive surgery has become standard for many medical operations. However, it comes with its challenges. For one, surgeons aren't always skilled. While some may be incredibly experienced, operations are still susceptible to human error—especially with rigid instruments. With new advents in soft robotics, soft robots are being explored for optimal surgery, better patient experience, and more effective diagnoses. The surgeons will no longer be responsible for instrumentation with soft robots, they mainly help with robot orientation, diagnoses, and interpretations of data provided by the robot. Soft robots are safer and more human-friendly, with gentler materials as well as fluidity that makes them apt for many circumstances. However, there are some issues in controlling their movement. In this paper, a learning-based kinematic controller was presented as the solution for a generic soft robot through a simulation. This model proved that it is possible to control a soft continuum robot through traditional techniques used for rigid robots. These techniques are optimized for soft robots through modern methods like machine learning by providing it data from motor babble. This discovery can be utilized for future models of soft robots built for minimally invasive surgery or other extensive uses. This will further development in the soft robotics field.

Keywords: Robots and intelligent machines, Control theory, Machine learning, Soft robots, Bio-robotics, Minimally invasive surgery, Inverse kinematics

1. Introduction

Soft robotics has started to gain significant popularity among scientists worldwide in recent years (Rus and Tolley, 2015). These robots exhibit greater capabilities than traditional rigid robots; their freer motion and adaptable structures allow them to interact with more delicate materials and navigate harder terrains (Mazumder and Singh, 2022). This is incredibly advantageous as it leads to more precision in a shorter amount of time. Explorers, scientists, doctors, and many other professions will be able to find a safer way to navigate and learn more. Especially in today's world, they have the potential to assist surgeries. Specifically, in minimally invasive surgery (MIS).

MIS is an endoscopic-style surgery, where the aim is to create smaller incisions and decrease recovery time (Mayo Clinic, 2023). Traditional methods involve doctor-dependent operations and rigid instruments. There has been significant progress in recent years and it has come to a level of using rigid, customized robots for such surgeries. Now, the biggest challenge that rigid surgical bots face is that their access to the body is limited by their flexibility and their components need incredibly skilled handling in order to avoid major injuries, making it a high-risk operation. Now there is a challenge of making MIS even more safe and efficient and this problem can only be solved by robots that are optimized for smaller and more delicate terrain (Althoefer, 2023). New solutions must involve more pliant materials. A common proposal over the years has been soft robots, as shown in Figure 1. However, the complication which comes up continuously for soft robots is the lack of a control strategy. While the flexibility brings major adaptability, it also poses issues with myriads of degrees of freedom, which makes it ultimately limitless in movement but much harder to handle and operate. There can be damage and pain caused by flexible devices such as soft robots

Vol. 2024 (11) 466 – 473
ISSN 2688-3651 [online]

like when doctors perform the looping of the colon during colonoscopy. It is also important to note that problems still exist with positioning, proficiency, force output, and the visualization of such tools. Without a proper command of this technology, it is impossible to implement it for surgical applications as motor babbling would result in a risk to patient health.

The topic of soft robots in surgery has been researched multiple times in the past. Russo et al. (Galvin, 2023) created a millimeter scale soft robot for tissue biopsy procedures, specifically targeted to helping solve lung cancer. She researched to find a low-cost method that would allow surgeries to go more smoothly for those with morbidities that prevent them from receiving anesthetics. This robot was a big example of how soft robots may be implemented in surgery; however, one of these has yet to be used in a real surgery due to risk of mechanical failure. A review published in the National Library of Medicine (NLM) considered soft robotics in MIS (Runciman *et al.*, 2019). It talked about the potential applications and obstacles today in order to further solutions for this field of robotics. It detailed the increase of interest in the topic since 2013, with over fifty papers driven to find a solution, many having continuum as their basic working principle. Runciman et al. discussed the limitations of all these solutions in depth, finding more flexibility was unfortunately inversely proportional to success. They concluded that complicated build and control were the two main issues. Another review published in NLM analyzed the potential of soft tissue surgical robots in MIS (Kim *et al.*, 2023). It found that wire-guided mechanisms, devices of remote control, and stereoscopic imaging would all be helpful to the success of these surgical robots but have yet to be implemented because of cost issues and a lack of communication between health professionals and engineers. However, this type of robot was also mostly rigid with instead more degrees of freedom than typical rigid robots and would still have some of the same issues as traditional solutions as discussed in the previous paragraph. There are a few solutions that have come up over the years that come close to ensuring these robots will go into MIS, but they were all held back by the barriers of modern soft robotics.

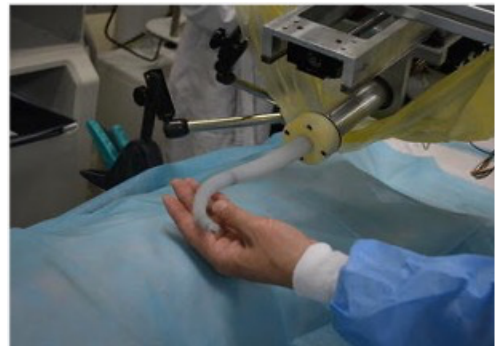
Figure 1. Application of soft robots to minimal invasive surgery (Wang et al., 2017)

Thorough research demonstrated that control is central to progress in soft robotics overall. To close this gap found over years, a control solution must be formed through more modern techniques. As technology becomes more advanced, newer ways to combat the issue have come up. The objective of this research is to find one of these methods and observe the possibilities of control. This paper hypothesized the possibility of controlling soft robots akin to methods used with rigid robots. Through a more conventional backbone, it will attempt to derive a unique way to control soft continuum robots in hopes of furthering efforts to implement them in MIS or even general surgery. To control a general robot, forward and inverse kinematic models must be formulated. Forward kinematics seeks to calculate the end-effector position according to the actuator joints, meanwhile inverse kinematics finds the joints according to the end-effector position (Murugesan, 2017). However, because of the compliance, redundancy, and various designs of soft continuum robots, it is difficult to develop a general kinematic framework. Solving inverse kinematics in soft robots is even more difficult due to the endless joint positions that can be used for a single target. The model will utilize the easier forward kinematics equations to find its joint angles given its target. The results will determine whether such an approach is reasonable for soft robots. While it will not be the exact same numbers and relations for every sort of soft material, if the strategy works for this digital model, it will prove the validity of a very similar method when applied to real-world materials and research may be furthered to resolve more advanced problems.

2. Materials and Methods

The model that was utilized had two modifiable joints with a third point at the end-effector. Figure 2 presents the model—a simulation of a soft robotic "arm" in MATLAB—which is surrounded by a blue ring to signify the small incision area in the patient body; the radii for the three parts of the robot were set as 0.05m, 0.04m, and 0.03m from

Vol. 2024 (11) 466 – 473
ISSN 2688-3651 [online]

bottom to top. The aim is for the robot to reach its target position through the ring, which is currently represented in the figure below: a modification of an old, unrelated simulation of a bionic handling assistant (BHA) (Rolf and Steil, 2012).

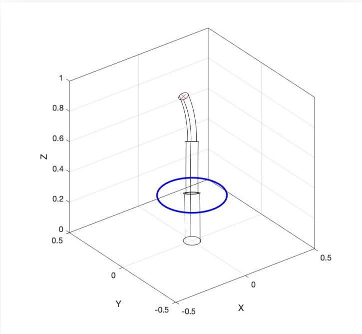

Figure 2. Soft robotic arm simulation model.

The model-free forward kinematics was developed through a mathematical approach to generate motor babbling. With motor babbling, the joints were changed by a marginal quantity to cause it to "babble" or moderately fluctuate every time in an arbitrary direction—basically making slight changes to the current positions of actuators. From here, the next step was to convert the forward kinematics model to an inverse kinematics model, which faced a few challenges.

2.1 Challenge 1: Trajectory-Planning

Surgical robots must be capable of traveling from outside the body to inside the incision with minimal collisions. This is important to ensuring a clean and safe operation. Without that accuracy, soft robots will not be capable of entering a surgical lab. Due to current limitations, further research must be done on trajectory planning for soft robots. Even rigid robots struggle with this and are still being tested for developments (Castro, 2019). Trajectory planning becomes especially difficult for soft robots with their lack of control strategy, which is essential to having proper movement to begin with. An aspect of general robotics that must still be resolved today when it comes to trajectory is the lack of camera vision, which would allow robots to be more autonomous. This may eventually go into soft robotics in due time, optimizing robot behavior.

One way to explore solutions for trajectory planning could be to build a soft robotic structure and capture its motor babble, and eventually train it on safer maneuvers for surgeries. The specific set of motions could vary depending on surgery and could even be coded into the robot so that it can avoid having to calculate new trajectories on the spot. Another possibility for exploration is where the BHA has a set of eight neighboring points (Xu *et al.*, 2022). These neighboring points will model a "workspace" for the robot and can be randomized. From here, the robot will choose the point of closest distance which has not been touched yet—given that prior locations have been stored. It will calculate the joints with a controller and move accordingly. As for adding camera vision to soft robots, there will need to be a lot of basic trajectory planning done first. Specifically for the delicate structure of a soft robot, the camera will have to be miniscule and of a light weight in order to be supported. This type of camera will need its own research and development.

Since trajectory-planning is not a goal of this paper, the trajectory was manually picked. This was done by using the original forward kinematics formula and iterating through its random generations to find values and orientations best suited to the purpose of this paper. This process must eventually be automated in the future to optimize work and eliminate as many inconsistencies to trajectory as possible. That is one of the next essential steps for soft robot implementations.

2.2 Challenge 2: From Forward Kinematics to Neural Networks

The first step of automation is to devise a faster and more effective forward kinematics method. Neural networks are the most practical because the data can be used to generate a forward model instead of doing manual tedious work of mathematical formulation, which would lead to discrepancies between the robot and the model due to inaccuracies of manual modeling. To train the neural network in MATLAB, it is necessary to have an arbitrary set of input values - which serve as the actuator positions. Then, there are the output values - which are the end-effector

Table 1. Training results for the neural network.

	Observation	MSE	R
Testing	7000	0.0009	0.9900
Validation	1500	0.0009	0.9889
Test	1500	0.0011	0.9880

Vol. 2024 (11) 466 – 473
ISSN 2688-3651 [online]

positions for those corresponding actuators. The data is trained to make connections between the positions of the soft robot and the end-effectors. The neural network that was trained led to the results shown in Table 1.

2.3. Challenge 3: From Neural Networks to Inverse Kinematics

Given these results, it was then important to figure out how to use the ability to guess the joint positions given any random end-effector positions. Standard inverse kinematic mathematic algorithms would lead to infinite degrees of freedom due to soft robot flexibility. Neural networks would also error out because of this and would return incredibly low and random accuracies (the R value in the table)—for example, 47%. There isn't much that can be done with neural networks in this case.

It was, however, possible to employ an optimization routine to develop the inverse kinematics solution. The function "fmincon" in MATLAB served the purpose in this paper (MATLAB, 2023). The function is used like gradient descent, which is a common method of optimization that minimizes error with a guess and check system, getting closer and closer to its answer. In this research, it was used to find the positions of the arm given the end-effector position. The main tool here was the forward kinematics neural network, which has the capability of finding the end-effector given position angles with a rate of approximately 98.8% accuracy. The function, fmincon, was given an arbitrary initial guess for joint positions and calculated the end-effector position with that guess and saw the difference between the expected end-effector position and the observed end-effector position. It created an—at first—arbitrary change to the guess and repeated the process of calculating error. Eventually, the function reached a point where its error was so low that it was inefficient and pointless to continue optimization; it stopped optimization. This returned a set of optimized points that the robot had to reach, in accordance with the goals that were set.

3. Results

After converting the simple diagram to inverse kinematics, evaluations were performed. Through the following experiments, the control strategy was verified.

For all of these experiments, the formula for mean squared error was utilized for evaluation. This method is a standard way to calculate the errors in models. For this paper, it was taken as an efficient path, reflecting the results of the finding properly and also presenting a simple but accurate procedure in assessing the model. The formula is below.

$$\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{1}$$

Where n represents the number of data points, Y_i represents the observed value, and $\hat{Y}_i$ represents the predicted value, respectively. This formula sums the square of the difference between the observed and predicted values for each point and averages them out. The difference is squared to remove negative change. For the purpose of this experiment, the observed values were the machine learning model's calculations and the predicted values were the points that were randomly picked.

3.1 Randomized Points

The first evaluation of this model checked for the mean squared error for a hundred scattered points within the range of the observer-visible 3D coordinate plane. First, the x-, y-, and z-coordinates were randomized, then the machine learning model was asked to find the joint positions for the soft robot. Once calculated, it found the error for each coordinate of every point, put them into an array and displayed them at the end. Then, all of the error rates were added up and averaged out. The result is given in the table 2. The control experiment resulted in minimal error for one hundred target points located anywhere within the bounds of the axes.

Table 2. Average rate of error for arbitrary points.

	100 Arbitrary Points
Mean Squared Error	0.001754

Vol. 2024 (11) 466 – 473
ISSN 2688-3651 [online]

3.2 Vertical Line Trajectory

In the subsequent experiment, the performance of the controller following a desired trajectory was authenticated where the path was set as a vertical line. The target z-value was randomized, while the x- and y-values remained the same. The merged graph in Figure 5 provides three different angles to view the resulting simulation. The mean squared error rate was about 0.00227, which is just a bit above the error rate for the experiment with a hundred arbitrary points.

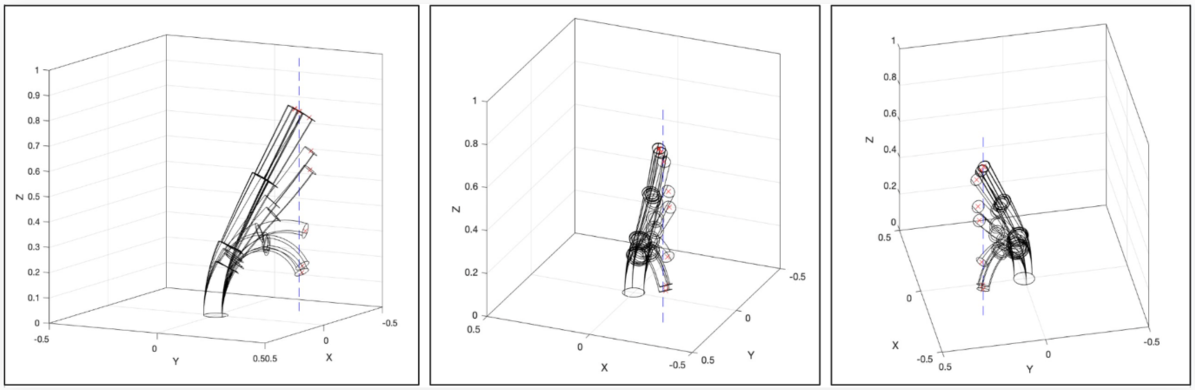

Figure 5. Accuracy of the Soft Continuum Robot on a line

3.3. Surgery-Based Modeling

The ultimate objective of this paper was to drive the robot into the simulated incision with precise control. Hence, fmincon was provided with the target end-effector positions from the trajectory plan of section 2.1. The function calculated predictions for the motion and then graphed these on the 3D plane. In Figure 6, six of these motions are displayed.

It is noticeable that the output motion was relatively similar to the manually chosen values that were mentioned in 2.1. with a mean squared error rate of 0.1108.

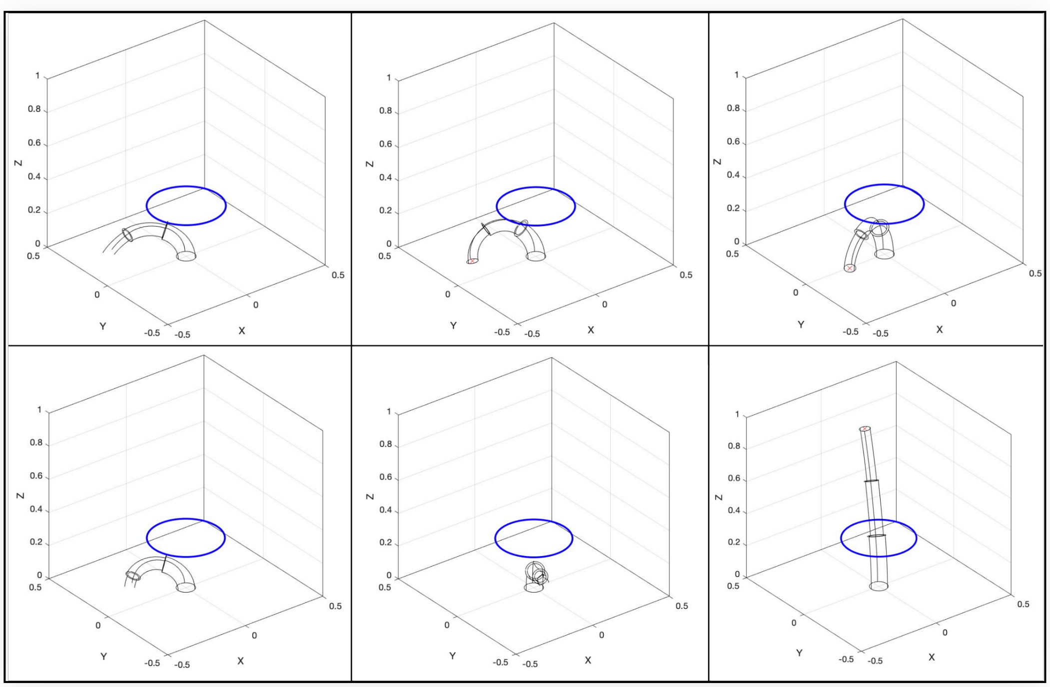

Figure 6. Accuracy of a Soft Continuum Robot in surgery.

Vol. 2024 (11) 466 – 473
ISSN 2688-3651 [online]

4. Discussion

This paper provided a simulation of a learning-based model for controlling a soft robot. This varies from past researches because it solely relied on machine learning and optimization algorithms rather than camera-based or equation-based procedures, such as PID controlling. It has been proven, with the accuracy of the experiments, that this control strategy works. There is a great possibility of its success in the real world.

4.1 Simulation Analysis

When the accuracies of each experiment are juxtaposed, it is possible to consider effective theoretical solutions to current issues with the control strategy for soft robots in general. These could, most importantly, enhance hospital efficacy and better the surgical system as the medical field utilizes more and more robotics daily.

In the first of accuracy tests, the average accuracy of calculating the actuator positions for a hundred arbitrary points was tested and received a low error rate, which is a testament to the fact that this robot—if implemented—would be capable of reaching random positions; it could eventually reach higher accuracies as well if trained on more data. This subject may be furthered through experimentation and research.

The second experiment, which was a test of the simulation accuracy in the bounds of a line, also proved well for the model. This demonstrated that, if given an algorithm to follow a series of movements within someone's body, the robot would be capable of achieving this with admirable accuracy. The advantage of this is less uncertainty with shaking fingers and needles during operations. Once a simple soft robot arm is constructed with a size minuscule enough to fit through small incisions, it could be tested to find expected positions through soft actuator manipulation similar to how it was done in simulation.

In the final simulation—Figure 6—it was seen that the soft robotic arm does not touch the blue ring, confirming its relative safety in situations like surgeries. The particular motion that was chosen could be the beginning of soft-robot-involving surgeries. Soon, the robot could be maneuvered to reach other points in the body through camera vision, decreasing shaky feed. This would benefit doctors as well as patients; doctors would be able to get a more stable idea of what the patient's troubling factor is and be capable of making more accurate predictions of what could have occurred in the body.

4.2 Future Impact

As discussed in the last section, the simulation can have multiple different applications. Its accuracy is a very important step to getting it implemented tangibly. Continuing from this research, the first step would be to create a real soft robot that would work well and similarly to the simulation, which would likely be an untethered or "free-like"-style—the safest option even if difficult (Jung *et al.*, 2024). In this scenario, it would be advisable to avoid soft robots with inflating bodies—like pneumatic expansion—which could cause the robot to be stuck in the body or even injure the patient.

A good next step after the creation of the robot would be to test its capabilities outside the patient—for example, having a fake body and/or fake organs to operate on. This will simulate the surgery experience and allow engineers to help make necessary changes to ensure its safety and good operation. This would also include giving the robot the code, initializing and defining a starting position. As discussed earlier in the paper, trajectory planning has many approaches and will be a significant next step to achieving application. One method of trajectory tracking or planning could involve making all motion relative to the start location. This would be helpful in finding the displacement of the robot which can tell surgeons when to stop the advance into the body. If the model is improved and tuned for a real-world robot, it will eventually become safe enough to be utilized in medical surgery.

Once the robot has been tested and can be vouched for, it can finally be implemented in surgery. In minimally invasive surgery, the robot might be affixed to a place near the surgical region, which would give it more stable ground for control. When it is placed right at the incision, the robot should be activated. During surgery, the robot will be capable of performing different types of fluid motion. This can entail laparoscopic surgery near the abdomen or pelvis

Vol. 2024 (11) 466 – 473
ISSN 2688-3651 [online]

where—through the incisions in the stomach—the soft robot will be inserted and be made to rotate around to observe the organs and possibly also resolve many different types of issues; for example, gallbladder removal, small tumor removal, or cyst, fibroid, stone, and polyp removal (Cleveland Clinic, 2024). There are many other types of minimally invasive operations like colorectal cancer, urologic, and hysterectomy surgeries (Kim *et al.*, 2023). What makes it so beneficial is how much more efficient and cleaner the operation can be. If the doctor guides the robot with external controls, a slight misstep would be much more tolerable since the material itself isn't too dangerous. Eventually, there will come a point in the world where soft robotics will be essential to healthcare and will improve the experience of surgery.

Besides the surgical aspect of this robot, it has many different types of applications too. It can be used for underground exploration—and, for this, the bot can be pneumatic to make the pathway easier to move through. This learning-based model may be applied for deep-sea exploration—places that humans have never seen before but where the soft robot will travel with ease due to its flexible and impressionable body. Another form comes in exosuits, which can help burden heavy loads or support people with back problems. There are still many other ways that this research may be applied to the medical field, such as gloves or other similar assistive technology for paralyzed and injured patients. A subset of these are rehabilitative robots, which can help create some resistance during exercise as they stretch—with rigid robots, this tension would be too forceful and can harm the person (Kaviri *et al.*, 2023). In surgery, soft robots can further assist by holding organs in place as surgeons operate on them. Overall, soft robotics has a big future.

5. Conclusion

The essence of this research was to create a reliable control strategy of a soft robot in minimally invasive surgery. Reliability in operation is imperative to: one, a safer and cleaner incision and two, more accurate diagnoses. This research led to the discovery of a kinematics framework for soft robots through gradient descent and neural networking, making it possible to convert forward kinematics to inverse kinematics. The accuracy of the method was tested through multiple experiments, which produced low error rates. These results reveal a valid approach to the control of soft robotics. This paper warrants further research in learning-based control of soft robots in order to lower error rates even further and eventually create a robot based on these principles.

Machine learning and artificial intelligence have an important role in today's world. As there is further development in this field, more models of soft robots will rely upon these discoveries. This research begins the journey toward more automated, efficient, and safe processes in the medical field as well as higher-achieving soft robots in all sorts of fields.

Acknowledgment

I must thank Dr. Thomas George-Thuruthel and Elijah Almanzor from the Cambridge Centre for International Research University of Cambridge (CCIR) for their incredible guidance in this project. I also thank CCIR for facilitating the education of high schoolers and working hard to help us all succeed with our projects. I know I couldn't have gotten as far all by myself.

References

Ahuja, N., & Thompson, J. G. (2022, September 24). *Minimally invasive surgery*. Yale Medicine. https://www.yalemedicine.org/conditions/minimally-invasive-surgery

Castro, S. (2019, November 6). *Trajectory planning for robot manipulators*. The MathWorks, Inc. https://blogs.mathworks.com/student-lounge/2019/11/06/robot-manipulator-trajectory/

Fmincon. Find minimum of constrained nonlinear multivariable function. (n.d.). MATLAB. Retrieved September 28, 2023, from https://www.mathworks.com/help/optim/ug/fmincon.html

Galvin, B. (n.d.). *Using soft robotics to increase safety and success in surgery*. Boston University Center for Information & Systems Engineering. https://www.bu.edu/cise/sheila-russo-soft-robotics/

Harvard BioDesign Lab. (n.d.). *Soft Robotics*. Harvard BioDesign Lab. https://biodesign.seas.harvard.edu/soft-robotics

Infection after surgery: Signs & prevention. (n.d.) UVA Health. Retrieved September 28, 2023, from https://uvahealth.com/patients-visitors/prevent-infection-surgery

Jung, Y., et. al. (2024). Untethered soft actuators for soft standalone robotics. *Nature Communications*, 15 (3510). https://doi.org/10.1038/s41467-024-47639-0

Kaviri, M., et al. (2023). Soft Robotics in Medical Applications: State-of-the- art, Challenges and Recent Advances. *ResearchGate*, Medical and Healthcare Robotics (pp. 25-61). Elsevier. https://doi.org/10.1016/B978-0-443-18460-4.00009-3

Kim, M., Zhang, Y., Jin, S. (2023). Soft Tissue Surgical Robot for Minimally Invasive Surgery: A Review. *Biomedical Engineering Letters*, 13(4), 561-569. https://doi.org/10.1007/s13534-023-00326-3

Laparoscopy. (2024, March 1). Cleveland Clinic. Retrieved July 1, 2024, from https://my.clevelandclinic.org/health/procedures/4819-laparoscopy

Mazumder, A., & Singh, A. (2022). *Kinematic Controller of a Soft Continuum Robot Using Learned Forward Models*. IEEE Xplore. https://doi.org/10.1109/URTC56832.2022.10002226

Minimally invasive surgery. (n.d.). Mayo Clinic. Retrieved September 23, 2023, from https://www.mayoclinic.org/tests-procedures/minimally-invasive-surgery/about/pac-20384771

Murugesan, M. (2017). *Simulation of Forward and Inverse Kinematics of a Robotic Arm*. Sacramento State Scholars. https://scholars.csus.edu/esploro/outputs/99257830798101671

Rolf, M., & Steil, J. J. (2012). *Constant curvature continuum kinematics as fast approximate model for the Bionic Handling Assistant*. IEEE Xplore. https://ieeexplore.ieee.org/document/6385596

Runciman, M., Darzi, A., & Mylonas, G. P. (2019). Soft Robotics in Minimally Invasive Surgery. *Soft Robot*, 6(4), 423-443. https://doi.org/10.1089/soro.2018.0136

Rus, D., & Tolley, M. E. (2015). Review of Design, fabrication and control of soft robots. *Nature*, 521, 467–475. https://www.nature.com/articles/nature14543

Soft Robotics revolutionise minimally invasive surgery. (2023, July 13). Queen Mary University of London. Retrieved July 1, 2024, from https://www.qmul.ac.uk/media/news/2023/se/soft-robotics-revolutionise-minimally-invasive-surgery.html

St John, A., et al. (2020). The Rise of Minimally Invasive Surgery: 16 year analysis of the progressive replacement of open surgery with laparoscopy. *JSLS: Journal of the Society of Laparoendoscopic Surgeons*, 24(4). https://doi.org/10.4293/JSLS.2020.00076

Wang, H., et al. (2016). A cable-driven soft robot surgical system for cardiothoracic endoscopic surgery: Preclinical tests in animals. *Surgical Endoscopy*, 31, 3152-3158. https://doi.org/10.1007/s00464-016-5340-9

Xu, Y., et al. (2022). Path planning and intelligent control of a soft robot arm based on gas-structure coupling actuators. *Frontiers in Materials*, 9. https://doi.org/10.3389/fmats.2022.1052538