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NEW TECHNOLOGY

Development of a machine learning-based tension measurement method in robotic surgery

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Abstract

Background Over 300,000 colorectal surgeries are performed annually in the U.S. with up to 10% complicated by anastomotic leaks, which cause significant morbidity and mortality. Despite its significant association with anastomotic leaks, tension is predominantly assessed intraoperatively using subjective metrics. This study aims to assess the feasibility of a novel objective method to assess mechanical tension in ex vivo porcine colons.

Methods This research was conducted using the da Vinci Research Kit (dVRK). First, a machine learning algorithm based on a long short-term memory neural network was developed to estimate the pulling forces on robotic arms of dVRK. Next, two robotic arms were used to apply upward forces to five ex vivo porcine colon segments. A force sensor was placed underneath the colons to measure ground-truth forces, which were compared to estimated forces calculated by the machine learning algorithm. Root mean square error and Spearman's Correlation were calculated to evaluate force estimation accuracy and correlation between measured and estimated forces, respectively.

Results Measured forces ranged from 0 to 17.2 N for an average experiment duration of two minutes. The algorithm's force estimates closely tracked the ground-truth sensor measurements with an accuracy of up to 88% and an average accuracy of 74% across all experiments. The estimated and measured forces showed a very strong correlation, with no Spearman's Correlation less than 0.80 across all experiments.

Conclusion This study proposes a machine learning algorithm that estimates colonic tension with a close approximation to ground-truth data from a force sensor. This is the first study to objectively measure tissue tension (and report it in Newtons) using a robot. Our method can be adapted to measure tension on multiple types of tissue and can help prevent surgical complications and mortality.

Keywords Biomechanics · Colorectal surgery · Machine learning · Robotic-assisted surgery · Surgical anastomosis · Tissue tension

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Over 300,000 colorectal surgeries are performed in the United States annually [1], with up to 10% being complicated by anastomotic leak or stricture [2]. Anastomotic leak is a serious complication of colorectal surgery, causing morbidity and mortality rates of 20–38% and 1–4%, respectively [3–6]. Survivors of anastomotic leak often face extended hospital stays, require additional interventions, and face lifelong disability, ultimately leading to more than double the total surgical cost [3, 7–10]. Due to the significant impact of anastomotic leak on clinical outcomes and quality of life, work has started teasing out anastomotic leak risk factors, which can be broadly classified as either patient-related (e.g., male sex, malnutrition, tobacco use, preoperative radiation, obesity, gut microbiome) or technical factors (e.g., tissue approximation, tissue perfusion, and anastomotic tension);

while patient-related factors have been studied and targeted with intervention programs (such as Enhanced Recovery After Surgery Programs), little progress has been made in standardizing and improving technical factors on anastomosis leaks [11–13].

In recent years, the importance of technique-related factors in the development of anastomotic leaks has become increasingly evident [14], but the role of technical factors, particularly anastomotic tension, in the development of leaks is still not well understood [12, 15]. Studies have found significantly higher odds of anastomotic leaks in individuals with higher body mass index [16–18] and lower anastomosis level/location [19–21], which may predispose anastomosis to increased tension. Although tension is considered a crucial technical risk factor, measuring it intraoperatively is challenging [22, 23]. Moreover, robot-assisted minimally invasive surgery has the added challenge of no haptic feedback. As a result, current methods of evaluating anastomotic tension rely solely on subjective visual assessment by surgeons [22, 23].

Despite tension being described as a crucial principle of operative techniques by Halsted over a century ago, there remains a gap in understanding its role in anastomotic healing. The absence of an objective method for measuring anastomotic tension during surgery represents an unresolved issue. Here we present the first stage of development of a machine learning (ML)-based tension measurement mechanism in robotic surgery. We started with algorithm development followed by validation in ex vivo porcine colons which we present here.

Materials and methods

Experimental setup

For this study, we utilized the da Vinci Research Kit (dVRK) comprising two patient-side manipulators (robotic arms) from the da Vinci Surgical System (Intuitive Surgical Inc. Sunnyvale, CA, USA) [24]. One arm held a Maryland bipolar forceps and the other a fenestrated bipolar forceps. These two instruments were used as these are some of the most common instruments used for grasping. We placed a Gamma force/torque sensor (ATI Industrial Automation, Apex, NC, USA) underneath a specially designed plate for mounting ex vivo porcine colon samples (Fig. 1). An expert robotic surgeon used the surgeon console to apply a random direction, but predominantly upward, force to 5 porcine colons for 1 experiment consisting of 5 trials each (25 total trials). Along with readings from the force sensor, we collected data on the robotic arm joint positions over time. The data on force readings, robot joint position, velocity, and torque were collected via the dVRK software [24].

Machine learning-based force estimation

As previously described [25–27], a long short-term memory (LSTM) recurrent neural network was trained to learn the joint torque during free space motion for each joint of the robot. Briefly, the network consisted of an LSTM layer with 128 hidden dimensions followed by two fully connected layers with rectified linear unit (RELU) activation. The input comprised a sequence of robotic arm joint positions read from encoders and velocities calculated according to Wu et al. 2018 [28]. Once the neural network learned the torque to move the robotic arms in free space (i.e., without contact), we subtracted the estimated torque from the measured torque at every time point to get the torque acting upon the external environment (i.e., with contact). We then multiplied the external torque with the spatial Jacobian at every time step to calculate the upward force exerted by each robotic arm. When using both arms, force is reported as the sum of the forces exerted by both arms. For more details on calculations and network training, see Wu et al. 2021 [25]. In summary, we used an ML algorithm to calculate force estimations based on robot joint positions. We then compared ML-based force estimations to measurements from the force sensor. To best approximate a real surgical scenario, we did not let the instrument hold and pull the colon tissue constantly. We extracted the periods that the robot instrument was in contact with the colon (i.e., starting from grasping and fully stretching the colon to the end of pulling), called "pulling trials."

Statistical analysis

The pulling force estimation was evaluated by calculating the root mean square error (RMSE) and standard deviation (SD) of each pulling trial, as described in Wu et al. 2021 [25]. We also calculated force range as the difference between the maximum and minimum force values during a pulling trial. Normalized RMSE (NRMSE) was calculated using the difference between force range and force estimation RMSE and dividing by the force range, as previously described [26]. Accuracy was defined as one minus NRMSE. Additionally, the Spearman's Correlation [29] was calculated to evaluate if the estimated force was correlated with the measured force (very strong: 0.90-1.00, strong: 0.70-0.89, moderate: 0.40-0.69, weak: <0.40).

Results

Across five different ex vivo porcine colon specimens (experiments), 25 trials were performed on the same day during which each colon was pulled upward with both

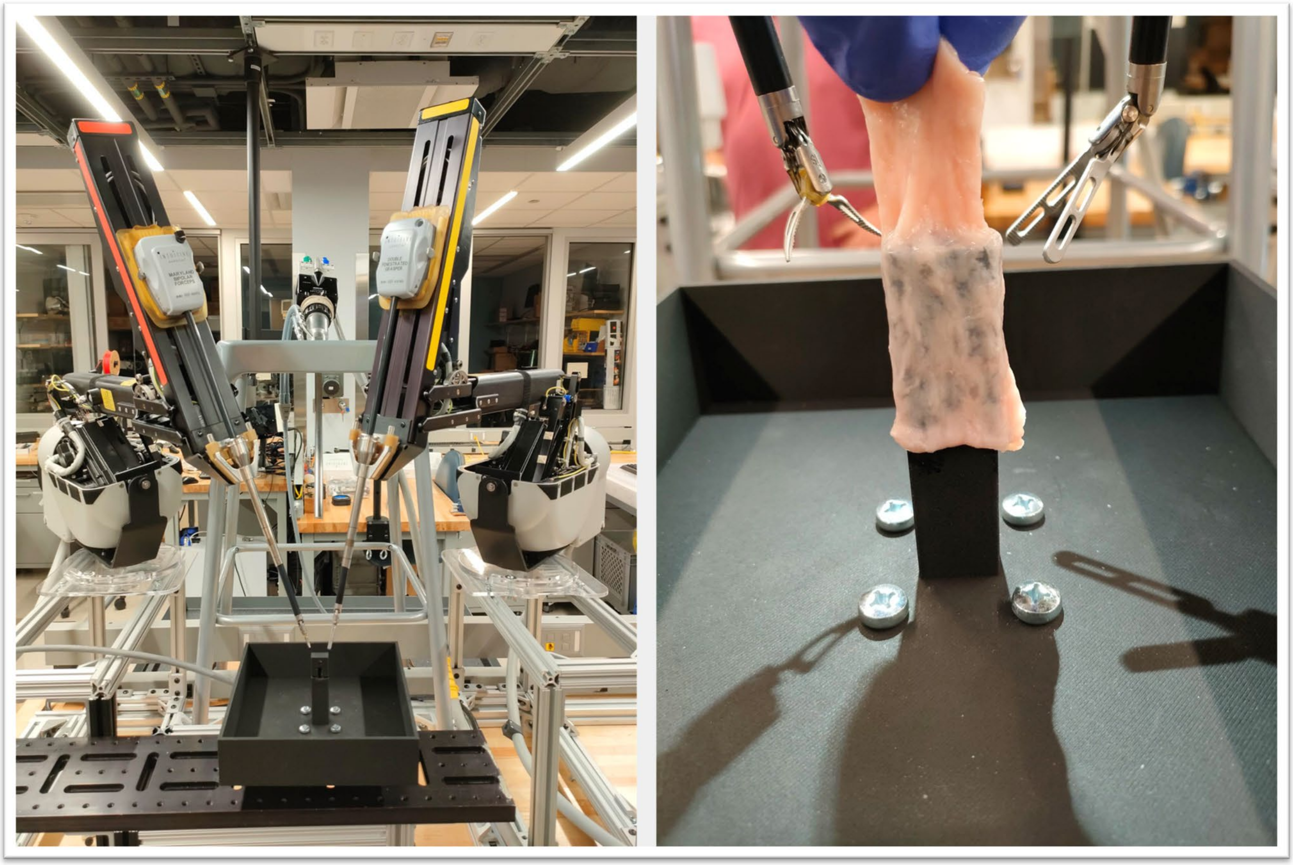

Fig. 1 Experimental setup. Left: da Vinci robotic arms over force sensor plate. Right: Close-up of porcine colon mounted on force sensor plate with da Vinci robotic arms on either side

robotic arms. Measured forces ranged from 0 to 17.2N for an average experiment duration of two minutes. Across the five experiments, the force estimation accuracy ranged from 65 to 81%, with an average accuracy of 74% (Table 1).

To better understand the results in a more approachable way, we analyze the best pulling trial from each of the five experiments. In Table 2**,** we display results from the best pulling trial from each of the five experiments. The highest force estimation accuracy achieved during a trial was 88%. Qualitatively, the measured ground-truth force from the sensor is shown to be very similar to the estimated force from our algorithm (Fig. 2), providing evidence that our algorithm can effectively track force variations exerted on the robotic arms.

Instead of plotting measured and estimated forces over time, we displayed scatter plots of estimated force by

Table 1 Average force estimation accuracy, error, and spearman's correlation for all colon-pulling trials across five experiments

	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5	All
Force Range (N)	6.57	6.40	8.07	4.58	7.06	6.54
Force Estimation SD[a] (N)	0.99	1.39	1.44	1.16	1.93	1.35
Force Estimation RMSE[b] (N)	1.23	1.73	1.60	1.45	2.04	1.61
Force Estimation NRMSE[c]	0.19	0.27	0.20	0.35	0.30	0.26
Accuracy (%)	81	73	80	65	70	74
Spearman's Correlation	0.87	0.81	0.86	0.84	0.64	0.80

[a]*SD:* standard deviation

[b]*RMSE:* root mean square error

[c]*NRMSE:* normalized root mean square error

Table 2 Force estimation accuracy, error, and Spearman's correlation for the best colon-pulling trials across five experiments

	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5
Force Range (N)	8.23	9.62	11.48	6.01	14.95
Force Estimation SD[a] (N)	0.95	1.72	1.63	1.16	2.98
Force Estimation RMSE[b] (N)	0.98	1.97	1.81	1.16	3.07
Force Estimation NRMSE[c]	0.12	0.20	0.16	0.19	0.18
Accuracy (%)	88	80	84	81	82
Spearman's Correlation	0.98	0.89	0.92	0.83	0.86

[a] *SD*: standard deviation

[b] *RMSE:* root mean square error

[c] *NRMSE:* normalized root mean square error

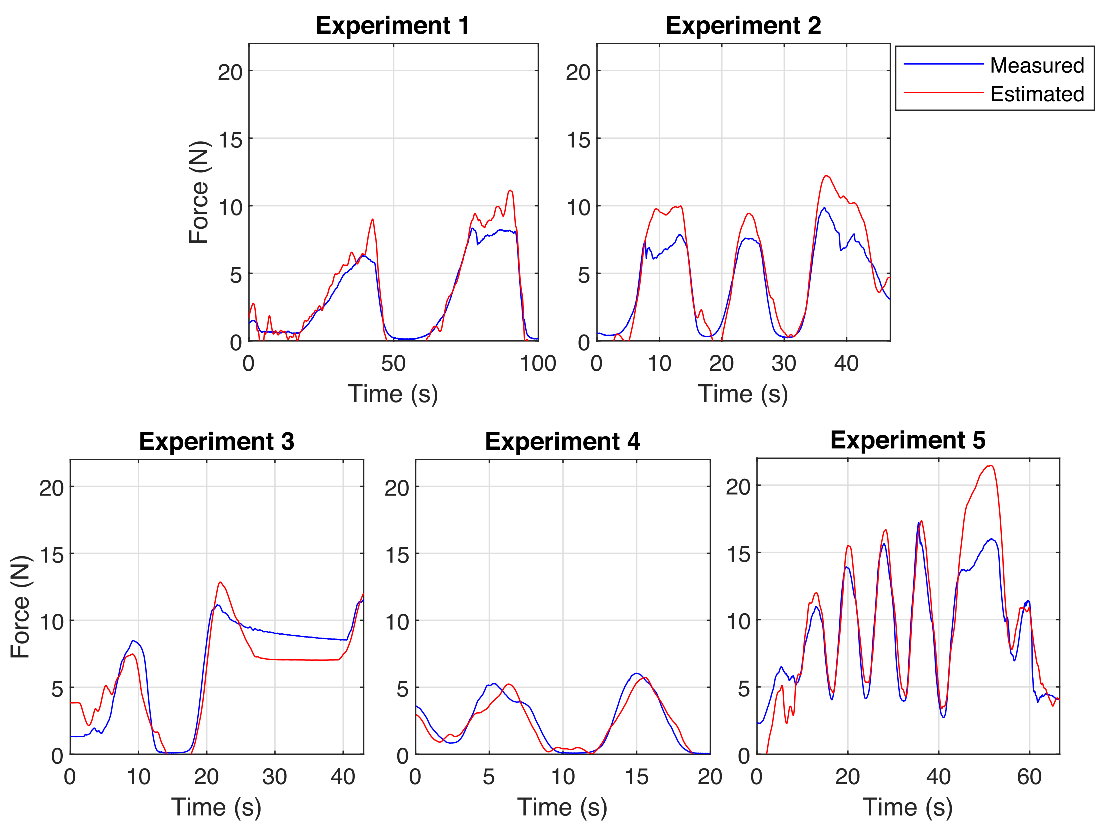

Fig. 2 Measured and estimated forces over time for the best colon-pulling trials across five experiments. *Note:* Colons were pulled for different amounts of time in each experiment

measured force as graphical representations of how we can quantitatively assess the relationship between measured and estimated force (Fig. 3). The scatter plots displayed data points being closely distributed around y = x, indicating a strong linear correlation. Spearman's Correlations were as high as 0.98, indicating a nearly perfect correlation between measured and estimated forces. No Spearman's Correlation was smaller than 0.80 across all experiments, showing that the estimated force maintains a strong correlation with the measured force.

Discussion

This study uses a machine learning algorithm to estimate pulling forces on ex vivo porcine colon across multiple trials within a low margin of error compared to ground-truth data from a force sensor. The results demonstrated an average force estimation accuracy of 74%, with the highest accuracy reaching 88% across trials. Spearman's Correlation between measured and estimated forces was

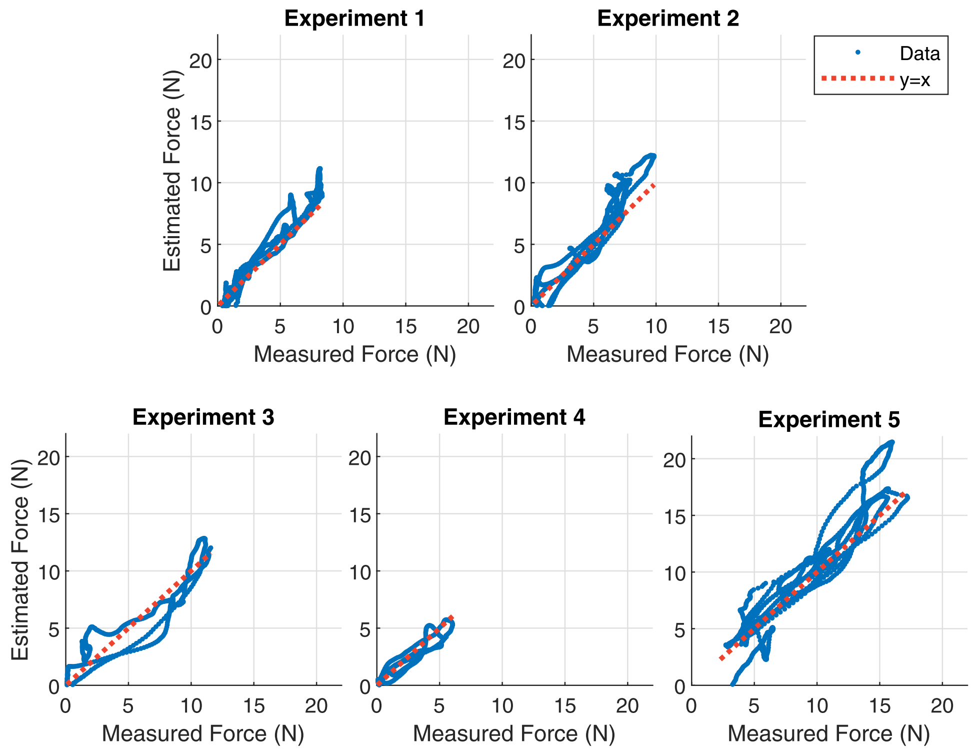

Fig. 3 Scatter plots of measured and estimated forces for the best colon-pulling trials across five experiments

consistently strong, with values as high as 0.98 and no values lower than 0.80 across experiments. These findings suggest that our algorithm can accurately track force variations in real time, providing a potential solution for overcoming the lack of objective force measurement in robotic-assisted surgeries. The strong performance across multiple experiments highlights the promise of ML in improving intraoperative assessments such as anastomotic tension measurement.

Our development of the first objective measurement of tissue tension during two-armed robotic surgery addresses a decades-old pain point in surgical practice. Techniques for assessing bowel viability and anastomotic leaks have remained a challenge in surgery along the gastrointestinal tract [15, 30], causing significant economic burden, morbidity, and mortality [3–10]. The majority of tension assessments have relied on the surgeon's judgment [11, 22]. Indirect tension assessments have included the level/location of the anastomosis, distance from the anal verge, and various intraoperative techniques [31]. More direct measurements included tensiometers or pulleys with weights on either end [32, 33], but these methods are destructive and thus unsafe for intraoperative use. Our algorithm can objectively assess anastomotic tension, improve operative techniques, and ultimately decrease the risk of morbidity and mortality.

Since the da Vinci V exhibits force sensing as a novel feature, this study is especially timely. Initial work has suggested that experienced surgeons, who were previously forced to rely on visual cues, apply different amounts of force even with the force-sensing feature active [34]. By offering a validated method for objective force measurement, this work bridges the gap between subjective surgeon experience and quantifiable data, providing a critical tool that can potentially reduce variability in surgical outcomes related to anastomotic tension. Moreover, as robotic surgery evolves, having robust systems for intraoperative force estimation will be essential in training the next generation of surgeons and improving overall surgical safety and efficiency. As the adoption of the new da Vinci V with force sensing technology becomes more commonplace, methods for assessing tissue tension will serve as invaluable adjuncts to aid in tissue tension estimation. Future studies can also aim to determine the maximal tension various types of anastomoses can tolerate before failing. Next steps include conducting trials on porcine colon anastomoses with intraluminal contents to more closely approximate real-world scenarios and test clinical applications. In addition to anastomosis testing, we aim to demonstrate the viability of intraoperative force sensing for tissue characterization, with the hope of catalyzing further research in intraoperative tissue modeling. Current work in Gaussian processes can be adapted to identify tissue compositions and provide additional information about the surgical scene.

Our pilot study exhibits some limitations. Compared to previous work [25], our colon-pulling experiments used tissue samples that exhibited more clinically relevant properties (e.g., tension, fresh liquid-covered tissue), so the sliding friction between robotic arms and the tissue surface may need to be accounted for in future iterations. Although a trocar and cannula seal were not used in this experimental setup, the neural network can be trained to compensate for these interaction forces [25]. Moreover, our force estimation method exhibits noise that worsens force estimation at smaller forces. Despite errors introduced by the dual-arm manipulation and tissue characteristics, our experiments exhibit similar accuracy to previous idealized experimental setups that involved a single-arm robotic instrument with rigid phantoms and exerting larger forces [25–27]. Additionally, each robotic arm exhibits individual differences. Each arm has slightly various levels of wear and tear, changing the electricity needed to supply a pulling force to the same degree. If our force estimation method were to be deployed clinically, this error would either need to be accepted, or we would have to tune the algorithm for each robot, which must be updated over time as the robots experience additional wear and tear.

Using the data acquired from colon-pulling trials ex vivo, we aim to validate this model in simulated surgical conditions by testing different types of anastomoses and incorporating simulated stool within the colons. Once established, our future research will focus on validating this mechanism in a human setting. We also aim to assess the correlation of our method with the new force-sensing technology. Additionally, our algorithm can be utilized in multiple other surgical specialties where tension plays a significant role in outcomes such as measurement of tension on the esophagus in thoracic surgery and fascia in abdominal wall reconstruction. Most importantly, future experiments aim to identify the clinical meaning of our tension measurements (e.g., the critical force at which bowel may be jeopardized). This will be a challenge as tissue from different subjects, as well as within the same subject but in different locations (e.g., cecum versus descending colon), will exhibit different properties. Future iterations must account for individual differences when applied in a clinical setting, for example, by calibrating the algorithm through a standardization procedure at the start of the case on the tissue to be used. In sum, we aim to continue refining this technology, applying it in different settings, and translating the measurements into clinically relevant data.

Conclusion

This study proposes an objective method using ML to measure colonic tissue tension using a two-armed da Vinci robot. With a Spearman's Correlation of 0.80 or higher between measured and estimated forces and an average accuracy of 74%, this method may offer a promising solution to reduce anastomotic complications by providing surgeons with quantitative measurements of tension. As the first real-time force estimation algorithm, our work addresses the longstanding issue of subjective tension assessments in surgery.

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Declarations

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