Haptic feedback for flexible endoscopic surgical robot using data-driven methods

Li, Xiaoguo

2021

Li, X. (2021). Haptic feedback for flexible endoscopic surgical robot using data-driven methods. Doctoral thesis, Nanyang Technological University, Singapore.
<https://hdl.handle.net/10356/152730>

<https://hdl.handle.net/10356/152730>

<https://doi.org/10.32657/10356/152730>

This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License (CC BY-NC 4.0).

Downloaded on 26 Apr 2023 20:48:41 SGT

HAPTIC FEEDBACK FOR FLEXIBLE ENDOSCOPIC SURGICAL ROBOT USING DATA-DRIVEN METHODS

**NANYANG
TECHNOLOGICAL
UNIVERSITY**

SINGAPORE

LI XIAOGUO

School of Mechanical and Aerospace Engineering

Robotics Research Center

Nanyang Technological University

2021

HAPTIC FEEDBACK FOR FLEXIBLE ENDOSCOPIC SURGICAL ROBOT USING DATA-DRIVEN METHODS

LI XIAOGUO

School of Mechanical and Aerospace Engineering

Robotics Research Center

Nanyang Technological University

A thesis submitted to the Nanyang Technological University in partial fulfilment of the
requirement for the degree of

Doctor of Philosophy

2021

Keywords

The keywords of this PhD research work are:

Surgical Robot, Flexible NOTES, Tele-operated System, Haptic Feedback,
Tendon-sheath Mechanism, Deep Learning, Hysteresis.

Abstract

Robot-assisted Natural Orifice Transluminal Endoscopic Surgery (NOTES) has been an emerging field of application in recent years and has demonstrated great potential and reliability in performing operations inside the peritoneal cavity while avoiding the necessity of abdominal incisions. It offers benefits such as enhanced operation precision, minimized tissue damage, and easier recovery for the patients.

To actuate the joints of end-effectors through narrow and tortuous paths, tendon-sheath mechanism (TSM) is widely adopted for flexible endoscopic robotic systems. However, the friction of TSM introduces nonlinearity and backlash hysteresis which degrades the control precision and creates hurdles for developing haptic feedback. It is difficult to mount force sensors on small end-effectors due to space limitation, wiring, and sterilization issues. Previous techniques for modeling the tendon-sheath system force transmission are associated with problems such as discontinuity when the system operates at the vicinity of zero velocity and complex ad-hoc parameter identification process. This study proposes a deep learning approach to predicting the distal force of TSMs based on proximal-end measurements. A TSM-driven robotic system manipulating biological tissue was developed to collect training and testing data for deep learning.

A two-stage data-driven method was developed to make dynamic distal-end force prediction of a flexible endoscopic robot without prior knowledge of its configuration. In stage one, a convolutional neural network is used to estimate the sheath cumulative bending angle based on the proximal-end force responses of the robot to a probing signal; in stage two, a combination of two long-short-term-memory models pre-trained for the bending angles nearest to the estimated angle (obtained in stage one) makes dynamic estimations of the distal-end force

of the robot. The proposed approach overcomes the challenges due to unknown TSM configurations and can robustly identify the correct force hysteresis phases of TSMs. The force prediction is continuous, robust, and has a mean RMSE of 0.1711 N. This method was validated on an actual flexible surgical robot.

Acknowledgement

First of all, my most sincere gratitude goes to my supervisor, Prof. Louis Phee Soo Jay. Under his tutelage, I have not only learnt how to conduct good research in a diligent manner but also evaluating novel ideas, making sensible decisions on which ones to pursue, formulating plan of attack, and attention to all nitty details which prove to be essential to the success of the study. All these are reasons why we love to learn about histories, read biographies of great people to summaries their idiosyncratic merits and mimic their strategies to success. But none of those comes close to learning from the smartest people in your life by the ways they analyse a novel problem, build up a project from scratch and dealing with unforeseen issues as the project progresses. These are the most valuable lessons of my Ph.D. candidature for which I am sure will positive influence a good part of my life. The best teachers, teaches beyond the academic subject and shape the way his students tackle challenges in their future careers.

Also, I am grateful to Prof. Tao Dacheng, Prof. Mao Kezhi, Prof. Ian Manchester, and Dr. Cao Lin for all your research guidance. It's been said by the 80-20 rule that 80% of your results are driven by the 20% of your effort. Logic will dictate that where we put our precious focus is going to steer our cause in the vast sea of knowledge. It's people like you that helped new sailors like myself to navigate in our academic endeavours.

Finally, I would like to extend my thanks to my colleagues in RRC lab such as Mr. You Kim San, Ms. Agnes Tan, Mr. Lim Chai Lye, Mr. Anthony Tiong, Mr. Liu Jiajun, Ms. Lai Wenjie, Ms. Huang Yanpei, and Mr. Phuo Thien Phan. Good work breeds accomplishment. I really enjoyed our work together and I'm sure you will go on and help many others.

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

15-Sep-2021

.....
.....
Date

NTU NTU NTU NTU NTU NTU NTU NTU
NTU NTU NTU NTU NTU NTU NTU NTU
NTU NTU NTU NTU NTU NTU NTU NTU
NTU NTU NTU NTU NTU NTU NTU NTU

[Li Xiaoguo]

Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

15-Sep-2021

.....
Date

NTU NTU NTU NTU
NTU NTU NTU NTU
NTU NTU NTU NTU
NTU NTU NTU NTU

.....
[Prof. Louis Phee Soo Jay]

Authorship Attribution Statement

(B) This thesis contains material from 3 paper(s) published in the following peerreviewed journal(s) / from papers accepted at conferences in which I am listed as an author.

Chapter 3 is published as Li, Xiaoguo & Cao, Lin & Tiong, AnthonyMengHuat & Phan,

Phuoc Thien & Phee, Soo. (2019). Distal-End Force Prediction of Tendon-Sheath Mechanisms for Flexible Endoscopic Surgical Robots using Deep Learning. Mechanism and Machine Theory. 134. 323-337. 10.1016/j.mechmachtheory.2018.12.035.

The contributions of the co-authors are as follows:

- Prof. Louis Phee provided the initial project direction and edited the manuscript draft.
- I am in charge of the overall problem solving strategy, benchmarking different potential solutions and data analysis.
- Dr. Cao helped to brainstorm the problem objective and potential solutions. In addition, I co-designed the experimental setup with Dr.Cao.
- I collaborated with Mr. Tiong to design the deep learning architecture used in the study and collection training data accordingly.
- Mr. Phuoc is responsible of manufacturing the designed experimental test bed for the study

Chapter 4 is published as Li, Xiaoguo & Tiong, Anthony & Cao, Lin & Lai, Wenjie & Phan,

Phuoc Thien & Phee, Soo. (2019). Deep Learning for Haptic Feedback of Flexible Endoscopic Robot without Prior Knowledge on Sheath Configuration. International Journal of Mechanical Sciences. 105129. 10.1016/2019.105129.

The contributions of the co-authors are as follows:

- Prof. Louis Phee suggested main focus of the study and edited the manuscript drafts.
- I wrote the drafts of the manuscript. The manuscript was revised together with Dr.Cao and Mr.Tiong.

- I performed the experiment with Mr.Tiong and Ms.Lai to collection training & testing data for the neural network.
- Mr. Lai helped to provide FBG technology for measure force in confined space.
- Mr.Phan designed the supporting test bed and saw the manufacture.

Appendix A is published as Cao, Lin & Li, Xiaoguo & Phan, Phuoc Thien & Kaan, Hung Leng & Liu, Jiajun & Lai, Wenjie & Huang, Yanpei & Huu Minh, Le & Miyasaka, Muneaki & Ho, Khek & Chiu, Philip & Phee, Soo. (2019). Sewing up the Wound: A Robotic Suturing System for Flexible Endoscopy. IEEE Robotics & Automation Magazine. PP. 10.1109/MRA.2019.2963161.

- Prof. Louis Phee provided the initial project direction and sponsored collaboration with Endomater for product development expertise.
- Dr.Cao and I were in charge of mechanical design of the robot, software development, experimental design, and data analysis.
- Mr.Phan Phuoc Thien helped to manufacture the surgical robot and perform daily maintenance.
- Mr. Liu Jiajun, Ms. Huang Yanpei, Ms. Lai Wenjie and Dr. Muneaki assisted with the crucial animal study execution
- Dr. Ho and Dr. Philip Chiu provided medical input regarding details of the surgery to be performed.

15-Sep-2021

.....
Date

NTU NTU NTU NTU NTU NTU NTU
NTU NTU NTU NTU NTU NTU NTU
NTU NTU NTU NTU NTU NTU NTU
NTU NTU NTU NTU NTU NTU NTU

.....
[Li Xiaoguo]

Table of Contents

Keywords	ii
Abstract.....	iv
Table of Contents.....	xi
List of Figures.....	xiii
List of Tables	xvi
Chapter 1: Introduction	1
1.1 Background	1
1.2 Context	3
1.3 Objective	5
1.4 Significance and Scope	7
1.5 Thesis Outline.....	9
Chapter 2: Literature Review.....	11
2.1 Development of robot-assisted surgery.....	12
2.2 Importance of Haptic feedback in surgery	30
2.3 Overview of properties of tendon-sheath mechanisms	36
2.4 Conventional mathematical modelling approach.....	38
2.5 Machine learning and medical robotics.....	41
2.6 Summary and Implications.....	47
Chapter 3: Research Design and Experimental Results for Known Configuration	48
3.1 Experimental Design	49
3.2 Methodology	52
3.3 Experiment Set-up.....	59
3.4 Data Analysis	61
3.5 PHASE I: constant speed, known sheath configuration.....	63

3.6	PHASE II: VARYING speed, known sheath configuration	72
Chapter 4: Research Design and Experimental Results for Unknown Configuration		
		81
4.1	The flexible endoscopic robotic platform	82
4.2	Methodology	91
4.3	Force estimation strategy.....	94
4.4	Stage One Results.....	103
4.5	Stage Two Results	106
4.6	Classification vs Regression.....	110
4.7	Robustness against bending angle distribution	113
Chapter 5: Conclusion and Future Works.....		116
5.1	Summary of Contributions	116
5.2	Novelties.....	1168
5.3	Future Work	120
Conference and Journal Publications		124
References.....		126
Appendices.....		141
Appendix A Development of the tendon-driven endoscopic surgical robot		141
A1.	System Overview	142
A2.	Needle Driver and Grasper.....	144
A3.	Control Architecture.....	147
A4.	In-vivo animal study.....	149
A5.	Summary	153
Appendix B SIMULINK code for data collection.....		154

List of Figures

Figure 1 The development of MIS.....	13
Figure 2 ZEUS telesurgery system	18
Figure 3 Da Vinci surgical system.....	16
Figure 4 RAVEN surgical robot	17
Figure 5 ViaCath system design	21
Figure 6 ViaCath system in-vivo porcine experiments.....	22
Figure 7 MASTER system illustration	24
Figure 8 Flexible surgical tools.....	24
Figure 9 The Over-The-Scope Clip, OTSC, Ovesco Endoscopy Inc., Germany	27
Figure 10 Hemoclips in operation.....	27
Figure 11 OverStitch.....	28
Figure 12 Tactile feedback device	33
Figure 13 Phantom Omni.....	33
Figure 14 Sigma.7 haptic device.....	34
Figure 15 A combination ExHand Box and exoskeleton device	35
Figure 16 TSM integrated in NOTES robot	36
Figure 17 Three cycles of force hysteresis profile.....	38
Figure 18 Modelling of a small section dx of a tendon and sheath.....	53
Figure 19 Modelling of sheath having different bending radius.....	54
Figure 20 Multilayer perceptron	56
Figure 21 Long Short-Term Memory	58
Figure 22 Schematics of experimental test bed	61
Figure 23 Experimental set-up.....	61

Figure 24 Prediction results and hysteresis profile	64
Figure 25 Zoom-in of one ANN prediction peak.....	65
Figure 26 Zoom-in of the modelling approach discontinuity between transition phase and releasing phase	66
Figure 27 LSTM force prediction	68
Figure 28 LSTM hysteresis profile	68
Figure 29 Transfer Learning force prediction.....	70
Figure 30 Transfer Learning hysteresis profile.....	70
Figure 31 Hysteresis profile under various velocities.....	73
Figure 32 Force predictions on five velocities.....	74
Figure 33 Training and testing trajectories	75
Figure 34 Force prediction over different trajectories	75
Figure 35 Movement and tension in TSM	77
Figure 36 Force prediction and hysteresis profile of new strategy	77
Figure 37 Force prediction on hand manipulation.....	80
Figure 38 TSM demonstration and hysteresis profile.....	83
Figure 39 Hysteresis profiles at various cumulative bending angles.....	85
Figure 40 Experimental platform.....	87
Figure 41 FBG sensors	89
Figure 42 Probing signal and recurrence plot.....	92
Figure 43 CNN and LSTM for force prediction	93
Figure 44 Stage one flowchart	95
Figure 45 Stage two flowchart.....	98
Figure 46 A demonstration of the force prediction strategy	101
Figure 47 (a) RPs sampled from load cell channel 1 across different cumulative bending angles. (b) RPs sampled from load cell channel 2 across different cumulative bending angles	104

Figure 48 (a) In order to construct RPs, auto-correlation is used to determine time delay, τ . (b) FNN is used to determine embedding dimension, m	104
Figure 49 Stage two prediction result	108
Figure 50 Accuracy comparison between diffused OHE, vanilla OHE, and regression.	111
Figure 51 Three different distributions with the same cumulative bending angle are demonstrated.	114
Figure 52 There are two common paths taken endoscopically during surgical operations, through the oesophagus and the large intestine.	114
Figure 53 The flexible endoscopic robotic suturing system	144
Figure 54 (a) instrument overview; (b)-(c) switching needle between two jaws; (d)-(g) stitching process.	145
Figure 55 Setup for the gripping force measurement when the pitch joint is rotated	149
Figure 56 In vivo animal study setup	150
Figure 57 Suturing process. (a) robotic arms deployed at the incision site (highlighted in the blue circle); (b) driving the needle through the tissue; (c) four stitches made; (d) create surgical knot by passing the needle through suture loops; (e) securing the knot by translating the robotic arms into opposite directions; (f) cutting the suture using an electric clutch cutter; (g) withdrawing the needle using the grasper; (h) incision closed using four stitches and a Surgeon's Knot; (i) needle taken out by the grasper.	151

List of Tables

Table 1 Prediction performance	63
Table 2 CNN bending angle predictions.....	105
Table 3 LSTM prediction results	106
Table 4 Vanilla OHE CNN results.....	110
Table 5 Regression CNN results.....	110
Table 6 Configuration with different bending angle distribution	113

Chapter 1: Introduction

This chapter presents the objectives of this research: *Haptic feedback for Flexible Tendon-Driven Surgical Robot using Data-Driven Methods*. This research focuses on obtaining distal tendon force without additional sensors for both the known and unknown sheath configuration scenarios. Section 1.1 is an overview of the current development of mainstream surgical robots and their advantages and drawbacks. Section 1.2 introduces the context of this research work while Section 1.3 elaborates the main purpose and scope of this work. The significance and novelty are shown in Section 1.4. Lastly, Section 1.5 includes an outline of the remaining chapters of this report.

1.1 BACKGROUND

Robotic-assisted Minimally Invasive Surgery (MIS) has been trending in recent years for various surgical procedures such as general surgery, oncological surgery, and colorectal surgery [1]. The introduction of modern surgical robots brings along many benefits such as enhanced operation precision, minimized tissue damage, tiny or no incision on the human body, and easier recovery for the patients. Robotic-assisted Natural Orifice Transluminal Endoscopic Surgery (NOTES), among all, shows great potential and reliability in performing operations inside the peritoneal cavity while avoiding the necessity of abdominal incisions. Phee et al. [2] developed a master-slave flexible endoscopic surgical robot that greatly improved surgeons' maneuverability within peritoneal cavities. A flexible endoscope is used to guide the slave robot arms to desired surgical sites while the master robot resides at the proximal end to actuate under the command of a surgeon. The development of NOTES has significantly helped patients to reduce pain, scar and achieve fast recovery. Notably, NOTES

has demonstrated many valuable features such as good precision, triangulation, and avoidance of unnecessary wounds. However, NOTES is proven to be more technically demanding over conventional open surgeries and laparoscopic surgeries. The main reason is the spatial limitation that this type of surgical robot is required to pass through the narrow, long and tortuous channel of the endoscope.

In the field of robotic actuation, pneumatic and hydraulic are often adopted as a power source for the robotic end-effectors since they provide decent actuation force while avoiding complex mechanisms. Unfortunately, in the realm of the surgical robot, these two approaches are not commonly used because of issues like leakage, fluid deformability, and control responsiveness. On the other hand, various catheters-based and gears-linkage mechanisms are devised to drive surgical robots [3, 4]. These designs enjoy advantages such as large payload force and excellent responsiveness, thus, are popularly used for laparoscopic applications. However, due to the spatial constraint of NOTES, gears-linkage mechanism fail to fit into a long and flexible endoscope channel. Therefore, to address the above issue in force transmission of flexible medical robots, it is common to locate the end-effectors away from the actuation units, such as electrical motors. Furthermore, tendon-driven mechanisms are usually considered to deliver force from external actuators to the robotic end-effector at the other end of the tendons. These mechanisms can be found in different types of robotic designs that address actuation spatial constraint as a priority including upper limb soft wearable exoskeletons [5], robotic grippers [6], and flexible endoscopic ViaCath system [7]. Bowden-cable actuation and tendon-sheath mechanism (TSM) are adopted to these systems so that the transmission mechanism is flexible, lightweight and capable of delivering large force.

TSMs usually consist of one or several sets of actuation cables (tendons) enclosed by hollow coils (sheath). Such mechanisms are small, robust and simple, suitable for delivering

high payload through long, tortuous and serpentine paths. These systems are blessed with compactness, robustness and good responsiveness. [8-11] On the other hand, with the existence of long tendon and nonlinear friction in the system, accurate control over the robot and providing haptic feedback information to the surgeon proves to be challenging. Extensive research have been conducted studying the intrinsic backlash hysteresis of TSMs, as well as possible compensations for motion control in continuum surgical robots. [12-13] However, obtaining dynamic distal force information of TSMs without integrating additional sensors remains a bottleneck to realizing haptic feedback for tendon-driven NOTES robots.

1.2 CONTEXT

Flexible endoscopic systems are commonly used in medical operations for both inspection and surgeries. NOTES robots are developed so that they can be delivered to surgical sites of interest with the minimum damage done to the patient's body. For these robot-assisted surgeries to be performed to their fullest potential, control precision and intuitive haptic feedback to the surgeon is paramount.

As the robustness, versatility, and reliability of robot-assisted NOTES rapidly improved over the years, the absence of accurate haptic feedback remained one of the major shortcomings. As a result, surgeons make decisions mainly based on visual feedback and experience [14]. Substantial studies have shown that providing haptic feedback to surgeons will not only reduce the cases of excessive or insufficient force maneuver to diminish tissue damage but also significantly shorten intraoperative time [15-18]. In reality, with the existence of nonlinearity and backlash in the robotic surgical system, the precise control and intuitiveness of the device are preternaturally hard to realize. Although there are various commercialized haptic devices available in the market such as Omega.7, Phantom Omni, and CyberGrasp [16, 19] that can provide decent haptic feedback for surgeons, what is missing

from the process is the interaction force information between the surgical robots and operated objects.

In robotic systems for NOTES, TSMs have been widely adopted for motion and force transmission because of their high level of flexibility and responsiveness of control in narrow and tortuous paths [2]. However, TSMs are intrinsically associated with issues such as backlash, hysteresis, and nonlinear tension loss due to the friction between the tendon and the associated sheath. As a result, gaining accurate haptic feedback is challenging for these systems. Various sensors, including sensors with working principles based on displacement, current, pressure, resistance, capacitance, vibration and optical properties [20], may be mounted at the distal-end of the a surgical robot to directly measure the interaction force for haptic feedback. However, these sensors are mostly limited by the availability of mounting space at the distal-end, harsh working environment during the surgery, sterilization capability, and issues with the associated wires and accessories, etc.

Alternatively, for TSM-driven robots, extensive efforts have been made to model the force transmission of the robot mathematically so that the force at the distal-end of the robot can be computed through the models using the measurements at the proximal-end. Kaneko et al. [21] analysed the tension transmission in TSMs based on Coulomb friction model. On the other hand, as the fitting performance of these modeling approaches improved, they mainly suffered from discontinuity between different hysteresis phases and inability to accurately describe the friction force when the system operates in the vicinity of zero velocity. In a more recent development of medical robots, Bouc-Wen model [22] has been pervasively used to model the nonlinear friction in TSMs. Such information is often used for backlash compensation in Bowden cable control to reduce hysteresis. [23-25] Do et al. [26] proposed a modified Bouc-Wen model with dynamic properties that employed velocity and acceleration information to depict the friction profile in an even higher precision manner. It

is noted, in the majority of literature, a spring was used to simulate the reaction of tissue. In reality, to practically implement force prediction on a haptic device, the non-linear property of tissue needs to be taken into account. Wang, et al. [27] compared tissue modeling methods including Voigt model, Kelvin model, Hunt-Crossley model and proposed a new approach to model the tissue force reaction under a constant indentation speed for TSMs in NOTES. In sum, in order to precisely predict the distal force in TSMs using mathematical models, a set of intricate parameters need to be carefully derived for the equations under the assumptions that the pretension of the tendon is large enough to prevent any system slacking, and the types of interactions with tissue are limited for each viscoelastic model to be built.

1.3 OBJECTIVE

Providing haptic feedback to surgeons operating robots for NOTES is proven to diminish tissue damage, shorten intraoperative time as well as improve device intuitiveness. However, mounting traditional sensors or encoders at the distal end of TSMs are extremely challenging due to the constraint of available space, medical sterilization requirements, and harsh working environment. Thus, it is difficult to obtain critical distal information through any physical sensors. On the other hand, force, displacement, and velocity information at the proximal side can more readily be measured using sensors that are located outside of the human body. Therefore, it is natural to consider estimating the distal information using available proximal measurement through the means of mathematical modeling. Extensive previous studies have been done using dynamic friction models like the Dahl, LuGre and modified Leuven to learn the force hysteresis of the TSMs and to make distal force predictions. These modeling methods demonstrated good accuracy under certain assumptions of the system. Because of these fundamental assumptions of various modeling methods and

the uncertainties that exist in the physical robotic system, these approaches are rarely used in practical operations. Therefore, the objective of this PhD work are three folds:

- To overcome the shortcomings of the conventional methods, a data-driven approach is proposed to train a deep Artificial Neural Network (ANN) with accessible sensory data from the proximal-end of a robotic NOTES system. The trained neural network learns the actual hysteresis profile of the TSM and make dynamic estimations of the distal-end forces by reading sensory inputs from the proximal load cell and encoder at each time step. This approach is proposed under the assumption that the Tendon-Sheath configuration is known.
- Secondly, in order to ensure the practicality of the approach, we need to develop a TSM-driven NOTES surgical robot to collect training and testing data ground truth data. In addition, we will validate the system's functionalities with an in-vivo animal study. The development of an actual surgical system is essential because it allows more realistic measurements rather than merely benchtop data collection.
- The third part of the objective includes developing a novel data-driven approach to identify an unknown TSM configuration (the path that a tendon takes to pass-through its corresponding sheath), exploring various measures to acquire distal forces as training data, establishing suitable haptic device to display the obtained distal force information to the operating surgeon and retrieving other meaningful information from the robotic system using data-driven techniques.

1.4 SIGNIFICANCE AND SCOPE

1.4.1 Significance

- Propose a novel deep learning approach to make force predictions on distal end-effectors of a tendon-driven NOTES robot or similar systems that incorporate TSMs. A good advantage of this approach is that there is no additional sensor required at the distal side.
- The data-driven approach make dynamic force predictions based on available sensory inputs from the proximal load cells and encoders. This approach needs neither intricate parameter identification process nor the assumption of no system slacking. Most notably, the prediction is not only highly accurate but also reflects the actual force hysteresis profile of TSMs.
- As there are various types of neural networks available, one important objective is to examine the performance of these algorithms in the field of surgical robotics when tackling time-series data. This objective includes the understanding of the data features that we can obtain from robotic systems without additional sensors and the compatibilities of different neural network architectures with these time-series data.
- The TSM's configuration has significant impact on its force hysteresis profile and elongation of associated tendons. Thus obtaining the configuration information of an unseen TSM is highly beneficial for both position and force control of Master-Slave robots as well as establishing haptic feedback.

- The proposed approach provides an estimation of the current system cumulative bending angle, it can also be used to facilitate the mathematical modelling methods which require information on the cumulative bending angle.
- Developed a flexible endoscopic robotic system for data collection and performance benchmarking. The system is successfully tested in an in-vivo animal trial to ensure its feasibility, thus, making the validation of the proposed approaches more realistic.
- This PhD work seeks to produce the end results of realizing haptic feedback for tendon-driven NOTES robot without additional sensors. Such an application will improve the device's intuitiveness, diminish cases of tissue damage and significantly shorten intraoperative time. In addition, as more and more data are mined from various surgical robotic systems, data-driven method can be applied to other possible areas such as control, automation, and surges recommendations for surgeons.

1.4.2 Scope and delimitations

In the first part of this PhD work, the author seeks to establish a novel data-driven approach to make distal force prediction by deep learning. To prove the concept, experiments were conducted on a 1-tendon-1-DOF system using identical instruments as the actual Master-Slave robot. The system was limited to a fixed TSM configuration and all forces exerting on the tendon does not exceed the normal working force range of NOTES robots. All data were collected and tested using a purpose built platform.

In the second part of the research, the identification of the TSM configuration will be explored. All experiments are designed to be carried out on the actual Master-Slave robot. To complete the whole cycle of force prediction, different approaches to acquiring distal forces

will be tested to provide training data for the above deep learning approach in the actual case. Finally, a hybrid architecture was developed where we firstly identify bending angles of the robot configuration, and then make a weighted prediction using 2 combinations of models from our pre-trained model portfolio.

1.5 THESIS OUTLINE

Chapter 1 introduces the background of surgical robots in minimally invasive surgeries and the motivation for this research, followed by the purpose, significance as well as the scope of this study.

Chapter 2 presents a literature review of the relevant field. It consists of five main part: the development of robot-assisted surgery, the importance of haptic feedback in surgery, an overview of properties of tendon-sheath mechanisms, the conventional mathematical modeling approach and the application of machine learning in the field of medical robotics.

Chapter 3 delineates the research design of known configuration study including: the design of experiments in two phases, the methodologies adopted in the experiments, the experiment set-up and the approaches taken for data analysis. There are 2 parts of experiments. In phase I, the tendon-sheath mechanism is operated under constant system velocity with 3 different approaches is applied to make dynamic predictions of distal-end force based on proximal information. In phase II, various system velocities and trajectories are explored. Finally, a robust training strategy is proposed for the artificial neural network.

Chapter 4 describes the research design of unknown configuration study including: platform used for the two-stage data collection method, FBG-based miniature sensor, actual surgical robot and its configuration set-up, and the technique of recurrence plot which is used for the signal processing of the probing signal. The method has two stages. In stage one, a convolutional neural network is used to estimate the sheath cumulative bending angle based

on proximal-end force responses of the robot to a probing signal; in stage two, a combination of two RNNs were used to make weighed prediction of the distal-end force based on bending angle estimation.

Chapter 5 summarizes the contributions of this research and emphasizes the novelties of the proposed approaches. Finally, several recommendations are made for the future work of this PhD study.

Chapter 2: Literature Review

This chapter presents a thorough breakdown of the background knowledge for the areas of interests for this PhD work. The literature review chapter delineates various theoretical supports from which the author develops a conceptual frame work for his hypotheses and formulates research target accordingly. There are four important fields of work involved in this topic. Section 2.1 reviews the current development of robot-assisted surgery. The review focus on two main aspects: *(i)* rigid tool surgical robots that are commonly used for laparoscopic surgeries. RAVEN surgical robot, ZEUS robotic surgical system and Da Vinci surgical system are presented for this type. *(ii)* surgical robots with flexible tools that operate through long and tortuous path which are illustrated by ViaCath system and the MASTER system. Section 2.2 presents the role of haptic feedback in surgical robotics and its impact on operation safety and precision. Section 2.3 provides a brief introduction of the properties of tendon-sheath mechanism which is pervasively used in the actuation of flexible robots. Furthermore, the friction characteristics associated with these mechanisms are illustrated. Section 2.4 shows conventional mathematical modeling methods developed to describe tendon-driven systems such as Coulomb model, Dahl model, LuGre model and Leuven's model. Lastly, the recent development of machine learning techniques and their applications in the medical field are discussed in Section 2.5. The characteristics of different machine learning approaches are analyzed so as to provide the foundation for the methodology of this research.

2.1 DEVELOPMENT OF ROBOT-ASSISTED SURGERY

Minimally Invasive Surgery (MIS) first emerged in the 1960s with the development of the rod-lens endoscope by Hopkins. Subsequently, MIS started to be established across most surgical disciplines and gain popularity. The goal of MIS is to minimize the number and size of visible body incisions thus improve overall cost-effectiveness. [28] In traditional MIS, visual and control precision suffers due to limitations such as 2-D video display, difficulty in instrument alignment as well as lack of haptic feedback. To remedy these shortcomings, robotic systems were introduced to the field to make possible improvements.

Robot-assisted MIS rapidly evolved in recent years in the surgical community. The robotic assistance brought in benefits such as reduced patient trauma, enhanced surgical precision, shortened surgery duration as well as faster patient recovery. The era of robot-assisted MIS commenced in 1994 when the first automated endoscopic system for optimal positioning (AESOP) prototype robot acquired US FDA approval. Ever since then, various surgical robots were fabricated targeting a wide range of surgical procedures in both laparoscopic and endoscopic surgeries [29]. In a robot-assisted MIS operation, instead of directly manoeuvring the surgical instruments, which is counter-intuitive, the surgeon operates a tele-manipulator device mapping its motion to the surgical instruments in a more intuitive manner. Tele-manipulator devices usually allow surgeons to move their arms, wrists, hands and fingers in 3-D space, and these movements are reflected on the robotic end-effectors for each degree of freedom (DOF). At the same time, visual feedback is usually provided for the surgeons by a steerable camera. Feedback vision could be in 2-D or 3-D depending on the demand of the surgery and the design of the robot. There are three categories of commonly used MIS procedures: intraluminal (surgeries taking place within the boundary of lumens), extraluminal (surgical tasks inside body cavity through small incisions, usually

conducted as laparoscopy), transluminal (commonly conducted with flexible endoscope via natural orifices such as mouth, anus and vagina, i.e. NOTES procedures). Figure.1 demonstrates the development of MIS in recent years [28].

Figure 1 The development of MIS

In the recent years the robustness and functionalities of robot-assisted surgical systems have been much improved and are capable of more complex surgical tasks including orthopaedic, laparoscopic, and cardiac surgeries. The integration of robotic assistance into surgical procedures not only enhances surgeons' surgical capabilities to access copious surgical sites while avoiding big incisions but also provides more direct and ergonomically optimal operating positions.

2.1.1 Laparoscopic Surgeries

Laparoscopic surgery is a modern surgical technique in which surgical tasks are conducted inside human cavity via small incisions. Despite various merits, in the recent years, advanced laparoscopy are proven to be technically more demanding for the surgeons to master than open surgery. Conventional laparoscopic surgery has a steeper learning curve mainly for two reasons: the laparoscopic surgeon is usually operating while viewing from a 2-D display on a distant monitor. In 2-D vision, the sense of depth is lost which is usually compensated by surgeon's experience. Furthermore, the steerable camera is maneuvered by an assistant. Thus the operating surgeon does not control his vision on the surgical site and has to constantly liaise with the assistant which lead to fatigue, miscommunications, as well as unsteady vision. [30] Hence, various robotic systems with multi-DOF end-effector and improved vision feedback were developed to address these shortcomings. A new generation of laparoscopic surgical robots are emerging such as RAVEN surgical robot, ZEUS robotic surgical system and Da Vinci surgical system. [31, 32] These systems are illustrated in detail in this section to delineate the development of robot-assisted laparoscopic procedures.

ZEUS surgical system

To improve the dexterity and operating precision of robot-assisted MIS procedure, Computer Motion established the ZEUS telesurgery system. Both 2-D and 3-D visualization systems were introduced to provide better spatial information while maneuvering instruments. It helped to transform the open surgery techniques into endoscopic surgeries and allow surgeons to use their familiar skills at the operating console. The system has demonstrated decrease in blood loss, tissue damage and patient hospitalization time. [32, 33] Corresponding study was conducted on the feasibility of both short-distance and long distance surgery using a tele-operating system. The bottleneck appeared to be the high-speed data transfer system due to quality video streaming in order to achieve timely visual feedback for movement coordination. [34]

A tele-manipulation robotic system enjoys many advantages such as scaling of movement (reduced ratio between surgeon's movement at master console to the actual movement of robotic manipulator), indexing (the system allows freezing of an end-effector while repositioning the tele-operator to an ergonomic position and then reconnect), enhanced ergonomics (comfort improved as compared to conventional laparoscopy) and tremor filter (remove the high-frequency movement of the surgeon's input). On the other hand, limitations also exist on the ZEUS system like the constraint of total endoscopic bypass grafting including the diminished internal and external work space. Intramyocardial target vessels are hard to detect and approach by endoscopic ultrasound probes. Furthermore, due to limitations on port positioning, the optimal working angles between end-effectors and camera are difficult to reach.

Figure 2 ZEUS telesurgery system

(a) Surgical tools, (b) Tele-manipulation console

Da Vinci Surgical System

Developed by Intuitive Surgical, Inc., Sunnyvale, CA, Da Vinci surgical system has proven to be one of the most successful tele-operated robotic surgical systems. The first prototype was setup in Europe in 1997. Since its inception, the system has been constantly upgraded especially the robotic arms, imaging system and control master console. The Da Vinci system leverages several advantages of conventional laparoscopic surgery while providing 3-D vision, ergonomic, intuitive control and wristed instruments that approximate the motion of the surgeon's hands. This system has demonstrated great superiority over conventional laparoscopy in surgical procedures such as urology and general and cardiothoracic surgery. [35]

The Da Vinci surgical system consists of three components: the robotic cart, the master console and the endoscopic stack as demonstrated in Figure.4 [29]. The robotic cart is connected to the manipulators through colour coded cables and was mounted on an easily manoeuvrable wheel base. A camera system was developed for this system with a dual lens and was spatially separated within 12-mm casing. Therefore, the system has two optical

systems collaborating together to provide true 3-D vision that most resembles human eye vision. The system's versatility largely comes with its wide variety of instruments that are readily changeable by the assistant surgeon. The robotic manipulators are mechanically and electronically balanced for easy use and safety. One robotic arm has six degrees of freedom and the changeable instrument provides one additional degree of freedom such as cutting or grasping. The surgical console has a binocular vision system that receives images from the dual lens. In addition, there are two master controllers and five foot-controlled pedals for robotic arm manipulation input. Lastly the endoscopic stack is in charge of providing high intensity light source, CO2 insufflation and image processing unit.

The Da Vinci surgical system is the most commonly used system across the globe for minimally invasive surgery. It is well designed for a wide range of laparoscopic surgical procedures and a relatively gentle learning curve for the surgeons. Despite its copious advantages, there still exist certain limitations such as backlash hysteresis due to friction force, the absence of haptic feedback in delicate operations or a flexible tool that allows the delivery through long and tortuous paths without severe bodily damage.

Figure 3 Da Vinci surgical system

(a) Robotic cart, (b) Master console, (c) Endoscopic stack

RAVEN surgical robot

In 2009, the BioRobotics Lab at University of Washington presented the RAVEN surgical robot. [36] RAVEN adopts the tele-operation principle involving the “master” at the surgeon site and “slave” at the patient site, as shown in Figure.2. At the patient site, there are two surgical instruments with 7 DOF. At the surgeon site, there are two portable PHANToM Omni devices used for tele-operation. The haptic device features 3-DOF force feedback, 6-DOF sensing as well as 2 momentary switches on the stylus. However, the RAVEN system does not handle well moving insertion points through abdominal wall.

Figure 4 RAVEN surgical robot

(a) Surgical tool, (b) PHANToM Omni devices

2.1.2 Endoscopic Surgeries

In Natural Orifice Transluminal Endoscopic Surgery (NOTES), rigid robotic manipulators, despite having advantages of good force transmission, are difficult to incorporate to certain systems that require small tool size and flexibility to pass through narrow channels. To tackle these challenges, a new type of robot was proposed for NOTES that incorporate flexible surgical tools which are usually delivered by using a flexible endoscope. The endoscope will carry the tools, enter the human body via natural orifices and pass through narrow and tortuous paths to the surgical site of interest. These tools commonly include cameras for vision feedback, insufflation and suction channels, light source and robotic manipulator to perform various surgical procedures. The robotic manipulators are usually designed to have multiple degrees of freedom so that they can easily steer, rotate and perform their functionalities such as cutting, grasping and suturing. The commonly used endoscopes for this application have length ranging from 60cm to 90 cm which means the flexible instruments must be longer than that in order to connect to their external actuation mechanism. In addition, the common endoscopes have tool channel sizes that vary from 2.8 mm to 6.0 mm. Among them, 2.8 mm and 3.2 mm are the most commonly used as channels to deliver robotic manipulators. Therefore the robotic end-effectors need to be even smaller to pass through. Due to the extreme size constraints, the integration of sensors of any kind is usually not in the picture. In the recent years of rapid development of flexible endoscopic robot, many have emerged targeting various surgical tasks, such as Endo-Samurai (from Olympus), Cobra (from USGI Medical), SPIDER (from TransEnterix), the ANUBISCOPE (from Karl-Storz), the DDES system (from Boston Scientific), the I-Snake (from Imperial College London), the R-Scope (from Olympus), the Incisionless Operating Platform-IOP (from USGI Medical), the HVSPS system (from Munich Technological University), the

ViaCath (from Hansen Medical), and the MASTER system (from Nanyang technological University) [37-42].

In the recent years, robot-assisted NOTES, as a novel technique, has gained significant attention from the medical field and is widely anticipated to define the next paradigm shift of surgical development. As a fusion of flexible endoscopy and advanced operative capabilities, this technology not only brings in the benefit of reduced scar and tissue damage to the patient but also is proven to diminish postoperative morbidity and enhance surgical outcomes. [42] By introducing robotic technology to the endoscopic system, it allow the separation of movement of the surgical instrument and the movement of the endoscope itself. In addition, there is marked improvement in the dexterity of surgical instruments, more precise control, better triangulation and reduced fatigue for the surgeon. In this chapter, we illustrate two of the typical tele-operated flexible robotic systems designed for NOTES: the ViaCath and the MASTER system.

ViaCath system

The ViaCath system is designed and fabricated by EndoVia Medical (Norwood, Massachusetts) to conduct endoluminal surgery. [43] The system consists of a long-shafted flexible overtube to deliver a endoscopic camera and two slave manipulators of 7 degrees of freedom that provide up to 3 N of force, on the other side of the flexible tube, a master console with haptic interfaces was used to input the surgeon's motion input. Therefore, the two distal end-effectors can easily perform tissue manipulation with good vision feedback. The ViaCath system utilizes DC servo motors to actuate its end-effectors and the power is transmitted by using pull-pull cable-conduit mechanisms and several pulleys. The robotic arms are 4.75 mm in diameter and provide ± 170 degrees rotation range to ensure optimal working space. Various end-effector types are specifically designed for surgical tasks such as grasping, cutting, needle holding and driving.

Figure 2 ViaCath system design

(a) Flexible articulated instruments (b) Surgical tools

The system was validated in in-vivo animal studies and proved its functionalities such as accurate end-effector manipulation, decent vision feedback, basic cutting and suturing capabilities as well as instrument exchangeability. However, the system has two main limitations. Firstly, it is difficult to guide the overtube to the desired surgical site in a precise

manner. Secondly, the lateral force provided by the instruments is only up to 0.5 N which may be insufficient during procedures happening in the GI tract. Thirdly, the system adopts a tendon-cable mechanism which inherently introduces nonlinear friction and system backlash hysteresis.

Figure 3 ViaCath system in-vivo porcine experiments

MASTER system

In the field of flexible endoscopy, another rising star is the MASTER surgical robotic system developed by Nanyang Technological University. The system was designed for Endoscopic Submucosal Dissection (ESD) and NOTES [44]. The MASTER system was developed in a way that allow collaboration between an endoscopist and a surgeon. The former is in charge of positioning of the endoscope including steering and orienting while the latter controls the motion of the two robotic end-effectors. In this way, the endoscope works together with the manipulator in order to provide sufficient work space for the surgical procedures. As shown in Figure.7, the system consists of a master console which is linked to a computer console, an actuation housing, a flexible endoscope with vision feedback used to deliver two slave manipulators and an endoscopic vision system [45]. The MASTER system also adopt the tele-operating strategy and use a pair of multi-degree-of-freedom joystick as input source. The left slave manipulator is an electrocautery hook for tissue dissection and the right manipulator is a grasper designed to grasp tissue and assist the left. The two distal manipulators have in total of 9 degrees of freedom and each degree of freedom is driven by two tendon-sheath actuation. At the proximal end, the tendon-sheath mechanism is connected to the motor housing to transfer movement and force. The maximum grasping force provided by the grasper could be up to 5.20 N which is sufficient to manoeuvre the slippery tissue in the GI tract. One special design is that the master console has an actuator in the grasping degree of freedom so that the surgeon could receive force feedback when opening and closing the grasper. The implementation of this feature ensures that the surgeon does not exert excessive force on the manipulated tissue in order to diminish unnecessary trauma.

Figure 4 MASTER system illustration

Figure 5 Flexible surgical tools

(a) Motor housing and flexible overtube (b) Gripper and cauterizing hook

The MASTER surgical robotic system is designed in tandem with a traditional endoscopic system to enhance the surgeon's capability inside human cavity. The system was validated through a series of in-vivo trial and human trials in both Hong Kong and India. It demonstrated excellent stability and robustness during surgeries such as ESD. On the other hand, the system has two main shortcomings that can be tackled in the future. Firstly, the system cannot implement force sensors at the distal end of the tendon which means the force feedback established can only be based on proximal information. Secondly, the system features enough end-effectors to carry out tissue manipulation and dissection. However, suturing of an incision can't be performed in cases of deep incisions or perforations.

2.1.3 Surgical Tools Used in Endoscopic Robot

Flexible endoscopy has drastically extended its reach from pure diagnosis to effective therapeutic treatments in the gastrointestinal tract over the years. However, these therapeutic treatments may result in significantly increased risks of perforations [46] with high death rates, e.g., the death rate of iatrogenic colonic perforations is as high as 5-25% [47, 48]. Secure closure of perforations is paramount to avoid leakage of gastrointestinal fluids into the abdomen which often leads to severe complications.

As flexible endoscopy plays an increasingly important role in therapeutic procedures, there is a rising demand for a reliable and effective endoscopic closure device in various procedures, from the widespread Endoscopic Submucosal Dissection (ESD), to Endoscopic Full-Thickness Resection (EFTR), and to Natural Orifice Transluminal Endoscopic Surgery (NOTES) [49]—a promising paradigm shift for minimally invasive abdominal surgery. ESD is an advanced endoscopic procedure to remove superficial gastrointestinal mucosa tumors through en-bloc resection. Requiring highly skilful operation, ESD has a high risk (up to 5-10% [49]) of perforations due to limited dexterity of tools and the lack of experience of the specialist. EFTR is an even more powerful procedure that removes tumours deep in the gastrointestinal muscular layer by resecting the full depth of the wall of the organ, which, however, results in a perforation requiring secure closure.

NOTES is an emerging endoscopic approach which obtains access to the abdominal cavity through natural orifices (mouth, anus, vagina, etc.) and subsequently through an internal incision in the stomach, colon, or bladder. Although no incision is made on the skin, an internal full-thickness perforation on the hollow organ is purposely created for NOTES internal access. All these procedures require effective endoscopic defect closure devices. In fact, despite the high potential as a paradigm shift, NOTES is still not widely adopted in

clinical practice, and one of the main reasons is the lack of tools for reliable, surgical-quality closure of defects [50].

Figure 7 Hemoclips in operation

Figure 6 The Over-The-Scope Clip, OTSC, Ovesco Endoscopy Inc., Germany

Hemoclips, as shown in Figure 8, normally used to stop gastrointestinal bleeding, are sometimes used for defect closure [51], but they are suitable only for shallow and small defects at the mucosal layer due to small closing force and opening range. Therefore, both industry and academia have made extensive research efforts to develop stronger and dedicated devices for defect closure in flexible endoscopy. Two devices are commercially available, i.e., the Over-The-Scope Clip (OTSC, Ovesco Endoscopy Inc., Germany) [52] and

OverStitch (Apollo Endosurgery Inc., US) [53]. OTSC is a large superelastic nitinol flexure clip mounted on the tip of the endoscope. As demonstrated in Figure 11, once released, OTSC can efficiently clip the defect (suctioned to the clipping area) with approximately 8-9 N force. If more clips or other tools are needed, the endoscope needs to be withdrawn for reloads or tool exchanges during the procedure. Furthermore, injuries to surrounding organs may occur due to suction, and the clip's position cannot be adjusted when misfired. OverStitch is the only device that can make running stitches for flexible endoscopy. Again, it must be mounted on the tip of the endoscope due to its large size, which requires endoscope withdrawal for tool exchanges. In addition, tying standard surgical knots is still not possible with OverStitch and thus a fastening element is employed to secure the stitches. Some other prototypes for endoscopic defect closure have also been developed, but they all have individual intrinsic problems that limit their clinical potentials [54].

Figure 8 OverStitch

Thus far, suturing with stitches and knots, the widely used traditional approach in open or laparoscopic surgery, is still not possible for flexible endoscopy. This unmet need might

be because of the confined and unstructured space of the orifice and target area, high levels of motion dexterity and force needed for suturing and knot tying, and critical size and strength requirements of wound closure. Emerging novel technologies, especially the evolving robotic platforms for flexible endoscopy [55] and the widespread da Vinci system, have fired up our imagination of using robotics technologies to overcome the challenges faced by endoscopic suturing. Robotics may benefit the suturing task with enhanced dexterity, larger forces, reduced tool size, and more intuitive control, leading to surgical-quality closure. Meanwhile, although many flexible endoscopic robotic systems [55] have been developed in the past decade, they are all for diagnosis or the removal of diseased tissue by cutting while the more complicated task—repairing the resulted wounds via suturing—are not possible with these systems.

Therefore, in Chapter 4, we will introduce a newly developed flexible tendon-sheath driven surgical that addresses these drawbacks. The new system has a few valuable traits such as dexterous (five degrees of freedom), through-the-scope, full-thickness puncturing, and the capability to perform running stitches. In addition, it serves another important purpose. We will be using this surgical system to collect training data and testing data for the data-driven methods and also validates their effectiveness in realistic scenarios. Detailed mechanical design is presented in Chapter 4.

2.2 IMPORTANCE OF HAPTIC FEEDBACK IN SURGERY

Robot-assisted MIS has demonstrated exceptional improvements in the evaluation of a combination of manipulation dexterity and accuracy, intraoperative time as well as minimizing trauma to the patients over traditional open surgery. However, the missing of haptic feedback is common among the current surgical robots including even the most pervasively used one, the Da Vinci Surgical System.

2.2.1 Haptics feedback

Haptics, generally referred to touch feedback, includes two main categories: force feedback and tactile feedback [10]. Force feedback in robot-assisted MIS is often defined as the measure or estimation of forces between the surgical instruments and manipulated tissue. The absence of such information results in the risk of insufficient force, excessive tissue damage or perforation outside the vision scope. The primary hurdle for this limitation is the difficulty to mount force sensors to the existing surgical robotic end-effectors. Although there are cases of success where specialized manipulators are designed to allow integration of force sensors [56, 57], they are not adopted in real-life applications due to problems such as sanitary issue, associated wires, cost, biocompatibility and harsh working environment inside human cavity. On the other hand, tactile feedback is used for detecting local tissue properties such as viscosity, surface texture and compliance. In many surgical procedures, the finger pad deformation, pressure distribution and contact location information play a vital role in the overall performance of the surgery as well as the comfort of the surgeon. [58] In addition, having tactile feedback helps a surgeon to evaluate the health of the tissue and locate possible tumors. As compared to force feedback, the latter received much less attention from the literature. There are more severe difficulties in realizing tactile sensors for surgical applications such as size and geometry (to allow fitting within the contacting surface of

manipulators), cost, biocompatibility and good surface finish to enable grasping and accurate sensing at the same time. Furthermore, due to the nature of available mounting space, wireless communication of data is preferred yet power cables are inevitable to be connected to the sensors. This wiring issue is problematic since we usually require an array of sensors which would involve a considerable number of cables. [59-61]

It was reported that providing haptic information to the surgeon enhances the outcome of manipulating the tele-operative system, improves the overall performance to justify elevated design complexity and cost, simplifies the execution of surgical procedures, and increases the comfort level of the surgeons. [62] While surgeons demonstrate various level of skill and comfort with these robot-assisted systems, operating surgical robots without feedback is particularly hard for surgeons who are accustomed to conventional open surgery. The absence of feel compels the surgeon to perform surgery constantly with unknown force. Although, some surgeons have reported that visual cues, like the deformation of tissue provide adequate information to assess the force being applied, the usefulness of the force and tactile feedback depends largely on the skill of the surgeon and the specific surgical procedures to be performed.

2.2.2 Development of Haptics Devices

In the robotics and virtual reality field, haptics is generally defined as the simulation and display of touch interaction between humans, robots and remote, or simulated environments. The ultimate objective of haptic technology in robot-assisted MIS is to develop “transparency”, that allows the surgeon to tele-operate a surgical device while feeling no difference from contacting the patient with his own hands. To implement haptic technology, two important elements need to be carefully designed: artificial sensors that measure haptic

information at the site of surgery and haptic display devices that convey these information to the surgeons [63]. In the conventional design of force feedback technology, motors are imbedded in the haptic device and are programmed to recreate the forces proportional to the interaction force of the manipulation. The modern surgical robotics manipulators have up to seven degrees of freedom including rotation, translation and grasping, etc. It is unusual to enable active feedback to all these DOFs as the missing of certain DOFs was proven to have little drawback [64, 65]. On the other hand, the fidelity and the stability of haptic devices is a trade-off. Since the motion dynamics of the master device and the surgical manipulator are not identical, it is impossible to achieve perfectly transparent tele-manipulator. Furthermore, there is likely to have time delay because of the time taken for the computer to process and transmit information.

Tactile feedback display to the surgeon allows the perception of direct contact between fingertips and contacting tissue or surgical instruments such as needles. The most direct design is to incorporate array-type tactile sensors that are individually actuated and their positions changes based on feedback information [66]. However, the drawback of this type of tactile display is that the manufacturing is challenging due to their small size and light weight. In addition, the integration of such devices might impede the movement of the master manipulators. Another unconventional way to display tactile feedback is to construct equipment that delivers well-controlled tactile illusions to the surgeon [67].

Figure 9 Tactile feedback device

Phantom Omni

Developed by Sensable Technologies, Phantom Omni is a 6 degrees-of-freedom commercialized portable master device. [68] It features a serial architecture, which means the handle is connected to the housing through a single serial chain. Phantom Omni is popularly used for virtual environment objects manipulation as well as haptic master manipulator for robotics tele-operative control. The device has a nominal resolution of 0.055 mm in its workspace and it allows active force feedback on 3 DOF, namely, the x-y-z axes.

Figure 10 Phantom Omni

Sigma.7 device

Sigma.7 is the most advanced master haptic device developed by Force Dimension. It has 7 active DOF on each arm, which means force feedback haptic could be established on all available joints in the workspace including translational base, rotational wrist extension and grasping unit. The active joints enable up to 20.0 N maximum force in translation, ± 8.0 N in grasping and 0.4 Nm in rotation. In addition, the master manipulator covers the natural range of motion of the human hand and features full gravity compensation. Such a design greatly reduces the fatigue of the surgeon during operation and provides copious room for customization for applications such as micro and nano manipulation, tele-operation console, virtual simulation and medical robotics. [69]

Figure 11 Sigma.7 haptic device

ExHand Box and CyberGrasp

A combination ExHand Box and exoskeleton device is another promising solution to haptic display. CyberGrasp is developed by CyberGlove systems LLC as a hand-grounded force-feedback device to display to human hand. To address the shortcomings of sole exoskeleton device application during tele-operation such as limited control bandwidth and position sensor resolution, ExHand Box is introduced to the system to customize controller implementation [70]. After post-processing the contact information, the performance was boosted to up to 50kN/m and 2kHz control loop frequency through MATLAB/Simulink. The device demonstrated significantly better haptic feedback when simulating the manipulation of a 3-D object than the above two hand-held devices.

Figure 12 A combination ExHand Box and exoskeleton device

2.3 OVERVIEW OF PROPERTIES OF TENDON-SHEATH MECHANISMS

TSM is one of the most popular transmission solutions for exoskeleton and surgical robots. It has revolutionized the use of flexible endoscopic robot because it's compact, lightweight, low cost and is capable of delivering high payload through long and narrow paths. TSM usually consists of two parts: a hollow helical coiled wire (referred to as sheath) and an actuation cable that slides inside the hollow sheath (referred to as tendon). Generally, the tendon is actuated by a proximal actuator by pulling, then it slides inside the sheath and transmits payload and movement to the other side of the sheath, known as the distal side. The distal side of the tendon is usually connected to the slave robot that perform the surgical procedures inside human cavity [25]. Figure.16 depicts the components of TSM and how it is integrated into the NOTES robotic system. NOTES robots usually have multiple DOF in order to provide sufficient manoeuvrability for the surgical task, and each degrees-of-freedom is commonly controlled by a pair of TSMs so that the slave manipulator moves both directions.

Figure 13 TSM integrated in NOTES robot

Despite the copious advantages that TSM brings to the NOTES robotic system, there are drawbacks that can not be ignored. The TSMs are inherently associated with problems

such as nonlinear friction, hysteresis and backlash. The magnitude of aforementioned effects is usually determined by a combination of factors such as tendon length, sheath configuration, tendon and sheath material, and the tendon tension and movement. [71] These negative properties usually create hurdles for accurate slave instrument movement control and realizing robust real-time haptic feedback. Proven by Sun et al. [72] that at the two extreme ends of the sheath, the compression force in the sheath is equal to the tension in the tendon at the same location. Thus, the proximal force (F_{prox}) is usually at the proximal-end of the sheath and the distal force (F_{dist}) is usually measured at the distal-end of the same sheath.

Figure.17 shows 3 cycles of TSM movement force profile from our own experimental data. The 3 cycles are randomly selected from data measured of a fix TSM configuration so as to demonstrate that the force hysteresis profile is consistent given a non-dynamic configuration. There are three distinct phases: ① the pulling phase: the tendon is being stretched, ② the releasing phase: the tendon is being relaxed, and ③ the transition phase: f_{TSM} changes its direction when the system operates near zero velocity, known as the deadzone. AI-Bender et al. [73] stated that the friction f_{TSM} in phase ① and ② depends on the relative displacement between tendon and sheath. Moreover, uniquely, the system enters a pre-sliding regime (micro-displacements) in ③, the transition phase which is characterized by the Stribeck effect. Researchers have found that the friction force f_{TSM} in phase ③ is a function of both displacement and previous history of displacement that form a non-local memory hysteresis [74].

Figure 14 Three cycles of force hysteresis profile

2.4 CONVENTIONAL MATHEMATICAL MODELLING APPROACH

In the development of tendon-driven robots, extensive efforts have been made to model the TSM mathematically. There are three key components that are vital to the behaviours of the system: the static friction, the dynamic friction and the sheath configuration status. One of the biggest challenges is to model the system behaviour when operating at near zero velocity or in stationary state. A limitation of several models is discontinuity in vicinity of zero velocity. This point will be further elaborated in the following content.

As the pioneers of this field, Preisach et al. [75] proposed the Preisach hysteresis model where hysteresis is seen as a form of non-linearity with memory which is popularly used in modern non-linear robotic actuator modelling [76]. Prandtl-ishlinskii model [77] is also often

used in scenarios where hysteresis is changing with respect to temperature. Kaneko et al. [21] developed a non-dimensional friction model based on a representation of hysteresis and system stiffness for tendon-drive robotics hands. The concept of discrete lumped mass model was adopted and the established model was a combination of static Coulomb friction model and the Hook's law describing a single TSM. Several assumptions need to be made, the sheath configuration must be fixed and the distribution of its curvature has to be uniform along the path. In addition, the initial pretension must be the same along the tendon. Kaneko et al. [21] had also made effort to model dynamic friction in TSM. The model was designed to address input-dependent stability observed during torque control of a tendon-driven robotic hand. Similar assumptions were made: large initial pretension, constant sheath configuration, and static Coulomb friction in this approach. The drawback of this model is clear, since the author only established linear relationship between the input and output force, inevitably, there will be discontinuity in the transition phase.

In the more recent literature, Palli et al. [78] integrated dynamic Dahl model with the Coulomb friction model to continue describing tension transmission in TSM with the concept of lumped mass model. The model demonstrated good results when comparing with different static and dynamic friction models in simulations but was consequently more complex to construct. However, since the model omitted backlash hysteresis from the function, its performance degrades from the previous version. In the follow-on work Palli et al. [79] proposed new modelling, identification, and control strategy for tendons sliding in curved pathways with considerations of friction and Maxwell viscoelastic effects. The model took into account the hysteresis in the transmission as well as characteristics of polymeric materials. The model incorporated the dynamic LuGre model to deal with the issue of discontinuity. However, similar to the two previous work, the TSM configuration was not taken into consideration which greatly limits the application of such an approach.

Theoretical models help to achieve good understanding of the friction force involved in TSMs and improve certain aspects such as control performance. There are a number of different models in the literature developed to describe the frictional phenomenon in tendon driven systems. Yet they suffer from certain disadvantages such as discontinuity in the transition phase, inability to capture nonlocal memory or Stribeck effects, and being highly complex when coming to real-life implementation. To address these shortcomings, Do et al. [24-26, 80-85] proposed a series of models based on dividing the friction properties into two typical regimes: the pre-sliding regime and the sliding regime.

Pre-sliding regime refers to the period when the sliding of two contacting surfaces commence their relative motion to the gross sliding. The relative displacement of the two surfaces is very small, and the friction force reflects a form of non-local memory hysteresis. In other words, the force magnitude is characterized by its path history. [86] Sliding regime, on the other hand, commences when gross sliding occurs and the friction force gradually increases to its highest value which is referred to as static friction. As velocity continues to increase, friction force will decrease. By considering the characteristics of the above effects, Do et al. proposed his novel models that predict dynamic distal force of TSM based on only proximal information. The approach provides smooth distal force predictions and was able to capture the force at near zero system velocity. The development of such methods are suitable for providing distal tendon force information in robot-assisted NOTES as well as improve the system tracking performances and backlash hysteresis compensation. Many experiments were carried out to validate the accuracy of these modelling methods in applications such as haptic feedback and advanced control strategies. The disadvantage of these approaches is that they require complex parameter identification processes by using ad-hoc combinations of various optimization strategies such as Genetic Algorithm and Nelder-

Mead Simplex method under the assumptions of constant pretention or excitation signal with constant amplitudes and frequencies.

2.5 MACHINE LEARNING AND MEDICAL ROBOTICS

Advanced technology and computing algorithms play an ever so important role in the evolution of modern surgery. Data-driven models are commonly used in engineering both with the descriptive goal of providing insights to available data and with the predictive goal of forecasting an important system variable. The application of machine learning (ML) in the field of medical robot is emerging in the recent years. [87, 88] The marriage of ML and surgical robots endow the latter with the capability to gain intuition from processing vast amounts of data and learning from demonstration, both of which are extremely difficult to realize by hard programming to robots. [89] Though the development of myriad ML techniques in the field of medical diagnosis and imaging process is rather mature and pervasive, they are not within the scope of the review. In this chapter, the main focus is on the ML application in the context of surgical robotics.

2.5.1 The motivation

There are increasing reports in recent studies regarding the application of ML technics in the field of surgical robotics. In particular, researchers take strong interests in using ML for the development of surgical tool in aspects such as understanding and modelling authentic surgical skills and to extract surgical workflow. The end results are aimed at realizing automation, human-robot collaboration, improvement of surgical outcomes and real-time decision making. [90]

Various robot-assisted robots have proven themselves to extend human capabilities in surgical procedures such as MIS. The integration of ML enhances these systems' abilities to perform smoother instrument trajectories, and to take over the execution of repetitive and time-consuming procedures so that the surgeon can focus on more skill-demanding tasks. There are a number of research declare success in automating simple surgical tasks with robotic systems, e.g., for suturing [91, 92] , tissue retraction [93] , knot tying [94]. Notably, all these algorithms are highly task-specific, one learnt technic does not generalize to others. In addition, parameter identification and trial-and-error paradigm are time-consuming tasks to perform.

ML techniques endow the machine with the ability to gain an intuition of complex systems by processing vast amounts of data. Xu et al. employed a data-driven approach to encoding system inverse kinematics in TSMs based on regression methods such as extreme learning machines, Gaussian mixture regression and K-nearest neighbours regression [95]. In the field of robotic manipulator control, He et al. introduced Iterative Learning Control (ILC) to address the vibration control for an Euler-Bernoulli beam system under aperiodic distributed and boundary disturbance [96, 97]. Zhao et al. compared the performances that several state-of-the-art deep learning (DL) algorithms have to offer when applied to monitor machine health using system data collected from low-cost sensors [98]. In these applications, ML is used to efficiently draw insights from the huge data-sets and assist human decision-making. Another popular application of ML is to build predictive models for important system variables such as force. Irgolic et al. applied multi-layer perceptron to make 3-D cutting force prediction of milling functionally graded material by CNC machine[99]. The force prediction has shown reliable results of less than 10 % error which allowed CNC machines to operate more safely. Researchers have applied different artificial neural network (ANN) architectures to replace complex mathematical models and express muscle activation

force dynamically based on electromyographic (EMG) signals [100, 101]. In the case of controlling an under-observed robotic system with uncertain compliant environmental contact, adaptive fuzzy neural network based control provides good robustness and stability [102]. To estimate the distal-end force in a tendon-driven NOTES robot, Li et al. proposed a DL approach that can produce accurate force predictions while identifying the correct force hysteresis profile [103]. However, like many conventional mathematical modelling methods in the literature, this approach works under the assumption of constant and known TSM bending angle. In a nutshell, there are emerging modern ML algorithms that demonstrate remarkable performances in tasks that were conventionally handled by mathematical models.

2.5.2 Machine Learning

ML develops rapidly in the recent years due to advancement in computing power as well as more readily accessible data in the modern society. The potential of this technique has long received attention in the robotic society, yet it is only recently that ML was considered for surgical robotics. In particular, ML techniques are used on surgical robots for skill learning and skill analysis. In ML for skill learning, the agent is provided with human expert generated data and is expected to learn the state and action mapping given the input. These applications are commonly achieved by the use of neural networks [104] and fuzzy nets [105]. Another approach of skill learning is by training the agent with trial-and-error paradigm. The agent is given an object, at the same time, rewards and punishments are associated with its interaction with its environment [106]. ML for skill analysis in robotic surgery includes structure assessment [107], outcome-based analysis [108], motion analysis [109], time action analysis [110] and error analysis [111]. In surgery, these evaluations provide valuable insight into the competence and skill level of clinicians. The aforementioned applications are realized

by using three main types of ML methods: supervised learning, unsupervised learning, and reinforcement learning.

Supervised Learning

In supervised learning, training data is provided as input vectors correspondingly labelled with its target. Such structure is ideal for building predictor model as the learner will be able to make reasonable target predictions from unseen new input vectors after being trained with similar data pairs and learn to generalize. The labelled training data usually come from actual measurements of robotic systems or human experts' demonstrations. The trained model can perform classification or regression on similar but unseen data. Popular applications in this area involve algorithms such as K-Nearest Neighbors [112], Support Vector Machines [113], and neural networks such as Convolutional Network [114] and Recurrent Network [115].

Unsupervised Learning

In comparison, in unsupervised learning, provided training input vectors are not labelled with a target. The common applications of such technique are to cluster similar data and to conduct feature extraction so as to reduce the dimensionality of the input vector. [116]

Reinforcement Learning

Another popular approach is reinforcement learning which deals with policies. Different from the first two, there is no training data prepared for the learning and the policies are learnt through a trial-and-error paradigm. Thus, learnt policies can act as strategies for the surgical robots allowing them to excel in real-time decision-making tasks. In reinforcement learning applications, the agent learns the optimal mapping between states and actions. This

learnt optimal policy represents how good it is for the agent to execute an action in a given state. [117]

Multilayer Perceptron

Multilayer perceptron (MLP) is a popular supervised learning technique in classification and regression applications in various tasks such as pattern recognition, speech processing, and optimization problems. [118] MLP is often used as building blocks of neural networks to pass on information between different layers or to extract key features from higher-dimension representation to a more concentrated representation. In many applications, MLP leverages its hierarchical structure to learn the representation in our training data and how to best relate it to the prediction once new input are given during inference time. It's capability of learning any mapping function is been supported mathematically by universal approximation theorem. [119]

Recurrent Neural Network

In the past few years, there is considerable advancement in artificial intelligence for applications like Google Translate and Baidu's text to speech technique. These problems share the similarity that the data they deal with is sequential data, which means each labelled data point does not stand alone and is associated with their adjacent data points. Similar to speech recognition and language translation problems, the input and output signals in the problem we sought to solve were time series sequential data.

Recurrent neural network (RNN) is a type of ANN that stands out when tackling time series problems. [120] In traditional feedforward neural networks, like convolutional neural networks and MLP, information only flows in one direction, from input to output. However, in a recurrent neural network, the output of a layer is fed back into the same layer together

with inputs of the next time step. With the built-in feedback loop, for each time step, RNN takes not only inputs from the current time step but also the information from all previous time steps, allowing it to act as a forecasting engine with a memory mechanism. On the down side, during back-propagation, RNN suffers from the vanishing gradient problem. [121] The weight receives updates that are proportional to the partial derivative of the computed error which can be vanishingly small after several multiplications by the chain rule. [122] This effect prevents RNN to learn efficiently since weight update becomes too slow, also known as the difficulty of learning long-term dependencies. To tackle this problem, Long Short-Term Memory(LSTM) is introduced that features a set of forget gate, input gate and output gate to regulate information going in and out of the cell state $C^{(t)}$ to handle the long-term dependencies. [123]

Convolutional Neural Network

In the recent revolution of the deep learning algorithm, convolutional neural network (CNN) is one of the most commonly used architectures that has demonstrated good efficiency in many fields including computer vision [124], natural language processing [125], and pattern recognition based on sensory data [126]. As a supervised learning algorithm, CNN is trained on a labelled dataset and learns a set of weights that minimizes the objective function (the error metrics) specified by the users. It can be built as a regression model that computes a system variable as its output, or as a classification model that produces an output in the form of a vector of categorical scores. The power of CNN lays in its ability to learn patterns within images and use these features to a variety of applications which are usually highly customizable. In addition, CNN computes at a faster speed due to GPU acceleration which is often considered as a lighter ANN as compared to RNN.

2.6 SUMMARY AND IMPLICATIONS

From the literature, it is evident that the development of robot-assisted surgery is rapid in the recent years. Together with the myriad benefits that these systems bring to the surgical field emerges several issues. This research focuses on one important element, namely the haptic feedback for surgical robots. In particular, the author seeks to establish the haptic feedback for NOTES robot that features TSM as the transmission method. Although a number of mathematical modelling approaches exist for this purpose, they suffer from several critical limitations and are not adopted in real-life applications. ML techniques, on the other hand, have demonstrate outstanding potential in handling problems involving large amounts of data. Thus, the author proposes to apply ML methods to complete the task of haptic feedback. In addition, the author look into solutions toward predicting the sheath configuration of the surgical robot which is not tackled in the previous research. The configuration information can also be used to facilitate the mathematical modelling methods which require prior knowledge on cumulative sheath bending angle or the assumption of known and fixed tool path.

Chapter 3: Research Design and Experimental Results for Known Configuration

This chapter presents the design adopted by this research to achieve the objectives stated in Section 1.3 of Chapter 1: acquiring distal-end force information by means of deep ANN based on accessible sensory data from the proximal-end of a robotic NOTES system. Section 3.1 discusses the methodologies used in this study; Section 3.2 details the different phases of experiment in which the methodologies were implemented, and the experimental workflow; Section 3.3 describes the two experimental set-ups that were used in this study: the actual tendon-driven flexible NOTES robot and the experiment test bed used for validation; finally, Section 3.4 discusses how the data was analysed and the limitations encountered in the process.

Section 3.5 details all the findings of this study. The results of the experiments are presented along with analyses on each individual experiment. By doing so, this chapter explains the logic behind the design of each test and demonstrates the importance of every experiment. There are two stages of experiments. In the first phase, the system velocity of the tendon-sheath mechanism was kept constant. The objective was to test and compare the performance of two types of deep neural networks. Afterward, the ANN with a better prediction accuracy was further investigated in its repercussion provoked by using a more accessible choice of training data formulation and the possibility of applying transfer learning. In the second phase, experiments were conducted to examine the magnitude of the impact of system velocity and trajectories on the force hysteresis profiles of a TSM. Both velocity and trajectories are considered within the normal working range of tendon-driven NOTES robot.

Subsequently, in regard to the new findings, a more robust data acquisition strategy was developed to train an ANN that was capable of making dynamic force prediction when TSM was maneuvered by human hand input.

3.1 EXPERIMENTAL DESIGN

3.1.1 Phase I: constant speed, known sheath configuration

To examine the proposed approach, experiments are designed in two phases. In the first phase, twenty-three pieces of tissue from different parts of two ex vivo porcine stomachs are mounted on the test bed and stretched by the tendon attached. Data $\langle d_{prox}, F_{prox}, F_{dist} \rangle$ is generated for supervised learning while each tissue is pulled by forces of various magnitudes for 200 seconds where $d_{prox}, F_{prox}, F_{dist}$ refer for the tendon movement at the proximal-end, the tendon force at the proximal-end and the tendon force at the distal-end correspondingly. The tendon movement speed is kept at a constant speed (2 mm/s) during data generation in the first phase of the experiments. This speed is normal for tendon-driven endoscopic surgical robots. One set is randomly chosen to be the test data set, two sets are randomly chosen to be the development data sets, and the remaining twenty sets are used to train the deep neural network models. Note that the input of the neural network $\langle d_{prox}, F_{prox} \rangle$ for training, development and testing sets are normalized with training mean μ_{train} and variance σ_{train}^2 to improve learning efficiency. $\langle F_{dist} \rangle$ is labelled as the target during training. Development sets are used to tune the hyper-parameters [127] of ANNs before we validated on the test set. The trained neural networks made predictions on $\langle \hat{F}_{dist} \rangle$ which are then compared with actual load cell readings to measure their performance.

The results of the ANNs are then compared with those of the mathematical modelling approach conventionally used in the literature. Subsequently, a series of follow-up experiments are conducted on the ANN with the best performance. We know that training the ANN with abundant data is beneficial to the prediction accuracy as well as the ability to generalize when unseen data is encountered during testing. However, collecting data from many tissue experiments is time-consuming and tedious. Therefore, we seek to explore the trade-off between data usage and ANN performance. First of all, the algorithm is further investigated in its repercussion provoked by using a more accessible choice of training data formulation. The analysis focus on the magnitude of prediction error, the depicted hysteresis profile and the ability to generalize.

In the fields of machine learning and data mining, there was a major assumption that the training data and testing data must be in identical feature spaces and share the same distribution. However, in the recent years, a new technique emerged as a novel learning framework that proved that the assumption is not necessary. [128] Transfer learning is a method in machine learning that focuses on storing knowledge learned from one problem (source task) and applying it to a different but related problem (target task). Such an approach brings benefits such as avoiding extensive data acquisition efforts [129]. It would make sense to apply transfer learning if the source task (ST) and the target task (TT) fulfil the following assumptions:

- ST and TT share the same inputs. In this case, inputs are the proximal load cell and encoder signals
- Low-level features from ST are helpful for learning TT. In our case, how the distal force changes in accordance with the input signals
- Training data for ST are more accessible than training data for TT

The last experiment in Phase I explores the possibility of applying transfer learning in the proposed approach in the context of collecting training data from a spring (ST) instead of stomach tissue (TT). Our application fulfils the three basic requirements of transfer learning. This method is considered because it alleviates the laborious data collection process as acquiring training data from a spring is much easier than that of many pieces of porcine stomach tissue.

3.1.2 Phase II: varying speed, known sheath configuration

In the second phase of the experiments, the effects of varying system movement, including velocity and trajectories, were further explored. Firstly, an experiment is conducted to examine the proximal-end force and distal-end force relationship of the same TSM setup operating under various system speeds. The normal system velocity of the tendon-driven NOTES robot ranges from 0.5 mm/s to 10 mm/s. Five different speeds are selected within the range, and their force hysteresis profile were plotted to look into the magnitude of the impact of the velocity. Follow up experiments were carried out to investigate if a neural network trained under constant system velocity was able to make reasonable predictions on the system with varying system velocity and trajectories. Subsequently, a set of experiments are carried out to examine the influence of trajectories of training tendon movements over the prediction results.

In order to train the ANN to make robust predictions on systems with varying velocity and trajectories, a more versatile training strategy was proposed to incorporate the computer-generated non-periodic excitation motor movement with varying velocity. The input of the ANN was set as $\langle d_{prox}, F_{prox}, v_{prox} \rangle$ so that it can learn and generalize the relationship between system velocity and force hysteresis profile during training.

During an actual operation of robotic-assisted NOTES, the motor movement is not as smooth as computer-generated trajectories. The jerkiness of human hand manipulation must be considered. The last experiment in this study was done to examine how well the proposed approach performs on estimating tissue manipulation force under a manually controlled motor movement through TSM.

3.2 METHODOLOGY

This research aims to acquire the distal-end force information of a NOTES master-slave robot that features TSM. The available inputs are limited to the existing sensors in the robotic system such as load cells at the proximal-end of the sheath and encoders on the actuators, namely the motors that drive the tendons. Three different approaches are considered in this work: the mathematical modelling approach, the Multilayer Perceptron, and the Long Short-Term Memory which is a type of recurrent neural network. The problem is essentially a prediction problem where the three methods make estimations of the distal-end force at each time step based on readings from the proximal side.

3.2.1 Mathematical modelling approach

To describe the undesirable characteristics such as system nonlinearity, backlash and hysteresis in the application of TSM, many mathematical modelling methods have been developed under different assumptions. Phee et al. [130] proposed a modelling approach for multi degrees-of-freedom tendon-driven flexible master-slave robot. This modelling approach is derived based on the mechanics of TSM and the associated dynamic friction. Researches in the field of medical robot implemented this method in order to establish haptic

feedback of the surgical robot with TSM, acquire tendon elongation information, and improve the tracking accuracy of distal displacement control. [8, 12, 72]

Figure 15 Modelling of a small section dx of a tendon and sheath.

Under the assumption that the bend has a constant radius, from the force balance on the tendon in Figure.18, we can obtain

$$T d\alpha = -N, d\alpha = \frac{dx}{R}, F = \mu N, \text{ and } dT = F, \quad (1)$$

Therefore

$$\frac{dT}{dx} = \frac{\mu}{R} T, T(x) = T_{prox} e^{-\frac{\mu}{R}x} \quad (2)$$

In Figure 18, μ stands for the friction coefficient between the tendon and the the associated sheath, N denotes the normal force acting on the tendon in this unit length, T denotes the tension in this tendon segment, C denotes the compression force on the sheath, R denotes the bending radius of the unit length, x denotes the longitudinal coordinate from the input end of the sheath to the present location, F denotes the friction in this segment and T_{in} denotes the tension at the input end of the tendon.

Figure 16 Modelling of sheath having different bending radius

In a flexible NOTES robot, the sheath follows the configuration of the endoscope and may form shapes with different bending radii throughout the entire length. Thus, we model the sheath as having n sections, each with its own radius of curvature $R_1 - R_n$ and segment length of $x_1 - x_n$ starting from the input end. Therefore the relationship between the input end tension T_{in} and the output end tension T_{out} becomes

$$T_{out} = T_{in} e^{-\mu\varphi} \quad (3)$$

$$\varphi = \frac{x_1}{R_1} + \frac{x_2 - x_1}{R_2} + \frac{x_3 - x_2}{R_3} + \dots + \frac{x_n - x_{n-1}}{R_n} \quad (4)$$

where φ represents the cumulative curvature from the master end to the slave end. Note that φ is a constant if the configuration of the endoscope remains unchanged throughout the operation. Once we have the value for φ identified, it is possible to establish the relationship between the proximal-end force and the distal-end force in the three distinct phases defined in Section 2.3 overview of properties of tendon-sheath mechanisms: ① the pulling phase, ② the releasing phase, and ③ the transition phase.

In the pulling phase, the proximal-end pulls the tendon acting at the input-end. Therefore,

$$T_{distal} = T_{prox}e^{-\mu\varphi} \quad (5)$$

Subsequently, we apply equation (6) to obtain the proximal-end tension at the termination of the transition phase $T'_{prox,tran}$. Then the duration of the transition phase is determined,

$$T'_{prox,tran} = T_{prox,tran}e^{-2\mu\varphi} \quad (6)$$

Finally, in the releasing phase, T_{prox} decreases and the slave-end will be “pulling” since $T_{dist} > T_{prox}$ in this case. Thus, proximal end becomes the T_{out}

$$T_{distal} = T_{prox}e^{\mu\varphi} \quad (7)$$

This method conveniently predicts the distal force information of TSM based solely on proximal load cell feedback and is used as the benchmark test before implementing deep ANNs.

3.2.2 Multilayer Perceptron

Multilayer perceptron (MLP) is considered in this experiment as a good candidate to make predictions on distal-force given proximal-force. There are three types of layers inside MLP: the input layer, the hidden layer and the output layer. The input layer takes inputs from the environment. In this case, the inputs are the motor encoder readings and the measurements from two proximal load cells after second-order low-pass filters and normalization as demonstrated in Figure 20. There can be one or more hidden layers in the MLP architecture, and the number of neurons inside these layers can be non-uniformly distributed. Finally, there is only one output layer has only one layer. There is only one output neuron which is fully connected to all the neurons in the last hidden layer. The output of this neuron $\langle \hat{\mathbf{F}}_{dist}^{(t)} \rangle$

reflects the distal force of the tendon. Each neuron is associated with a nonlinear activation function except for the ones inside the input layer.

Figure 17 Multilayer perceptron

The information between the neurons is computed as follows:

$$output_j^{(n)} = \sigma^{(n)}(\sum_i output_i^{(n-1)} W_{ij}^n + b_{ij}^n) \quad (8)$$

The $output_j^{(n)}$ is defined as the output of $neuron_j$ in $layer^{(n)}$ computed from the activation function $\sigma^{(n)}(\cdot)$. $W_{ij}^{(n)}$ and $b_{ij}^{(n)}$ are the weight matrix and bias associated with $neuron_j$ and $neuron_i$ in the previous layer.

MLP utilizes back-propagation in the training process. [131] The error is computed using the predicted force $\langle \hat{F}_{dist}^{(t)} \rangle$ and the actual measurement from the load cell $\langle F_{dist} \rangle$. The error is then back-propagated through each neuron after feeding in a batch of training data whose size is predefined. Finally, the weight matrix and bias $W_{ij}^{(n)}$, $b_{ij}^{(n)}$ are updated accordingly.

The weight matrix and bias are known as parameters of the MLP. However, they are not the only factors that affects the output of the neural network. There are a number of hyper-parameters that also play important parts in the performance of MLP in the context of the problem assigned. The number of layers and distribution of neurons in each layer greatly affects how well the model learns the training data and generalizes on the testing data. The activation function $\sigma^{(n)}(\cdot)$ is the source of non-linearity in the architecture, and it determines how each neuron fires up its output. Three commonly used activation functions are considered in this study: sigmoid, tanh and ReUL. A batch size is predefined before the training to specify how often the back-propagation is executed. A learning rate is set for the network that conditions how much to update the weights and bias in ratio to the error during back-propagation. The bigger the learning rate the faster the network learns. However, if the learning rate is too big, the training might never converge. The final architecture adopted in this research will be discussed in Chapter 4.

3.2.3 Recurrent Neural Network

Figure 18 Long Short-Term Memory

Figure.21 demonstrates the architecture design of LSTM used in this work for distal-force prediction when unfolding in time. The LSTM takes input signals of the current time step from the load cell and encoder along with the previous prediction $\hat{F}_{dist}^{(t-1)}$ to make a prediction $\hat{F}_{dist}^{(t)}$ for the current time step. The forget gate, input gate, and output gate are denoted by ‘f’, ‘i’ and ‘o’ respectively. Each of these gates has its weight matrix and bias.

The forget gate learns how much to forget from previous cell state and the input gate determines how much new information to let in for current time step, where W_{cand} and b_{cand} are weight and bias for candidate layer tanh:

$$f^{(t)} = \text{sigmoid}(W_f \cdot \langle \hat{F}_{dist}^{(t-1)}, d_{prox}^{(t)}, F_{prox}^{(t)} \rangle + b_f) \quad (9)$$

$$i^{(t)} = \text{sigmoid}\left(W_i \cdot \langle \hat{F}_{dist}^{(t-1)}, d_{prox}^{(t)}, F_{prox}^{(t)} \rangle + b_i\right) * \tanh(W_{cand} \cdot \langle \hat{F}_{dist}^{(t-1)}, d_{prox}^{(t)}, F_{prox}^{(t)} \rangle + b_{cand}) \quad (10)$$

The Cell state is the long-term memory; it represents all of the learning done in previous time steps:

$$C^{(t)} = f^{(t)} * C^{(t-1)} + i^{(t)} \quad (11)$$

Finally, the output gate is the attention mechanism that decides how much information to output from the cell state $C^{(t)}$ and $\hat{F}_{dist}^{(t)}$ is computed through an identity activation function $g(\cdot)$:

$$o^{(t)} = \text{sigmoid}\left(W_o \cdot \langle \hat{F}_{dist}^{(t-1)}, d_{prox}^{(t)}, F_{prox}^{(t)} \rangle + b_o\right) * \tanh(C^{(t)}) \quad (12)$$

$$\hat{F}_{dist}^{(t)} = g(W_F \cdot o^{(t)} + b_F) \quad (13)$$

The prediction $\hat{F}_{dist} = \langle \hat{F}_{dist}^{(1)}, \hat{F}_{dist}^{(2)}, \dots \rangle$ forms a smooth signal to reflect the algorithm's prediction at each time step.

3.3 EXPERIMENT SET-UP

The main purpose of this work was to investigate the performance of the deep ANN approach for TSM distal force estimation during tissue manipulation. As shown in Figure. 22 (b), a test bed was devised to generate training and validation data to examine the performance of deep ANNs experimentally. A DC motor (2657W024C R from Faulhaber Schonaich®) was employed to actuate the tendon from the proximal end. A motor encoder (HEDS-5540 A14, 500 CPR, accuracy 0.18°) obtained the actual displacement and velocity of the tendon d_{prox}, v_{prox} . For all experiments, the DC motor was under closed-loop PID

displacement control using feedback from the proximal encoder. A 0.45 mm diameter tendon (Asahi Intecc®) was used in the test bed to transmit movement to the distal side via a sheath (Asahi Intecc®) of 1.14mm diameter. Two FUTEK LTH300 (capacity 222 N, accuracy 0.007N) compression load cells were attached to both the proximal and distal ends of the sheath, respectively, to measure the sheath compression force during the operation. It was proven by Sun et al.[72] that the tension in the tendon is equal to the compression force in the sheath. Therefore, F_{prox} and F_{dist} were acquired as the corresponding proximal and distal tension of the tendon. At the distal side, a piece of tissue was mounted between the end of the tendon and a fixed stand. Sensory feedback was acquired and synchronized by MATLAB SIMULINK interfaced with a QPIDe data acquisition board from Quanser Quarc®. We used 1 kHz for sensor reading sampling and analog output processing which is sufficient for the application. All instruments have identical specifications as those used in the actual master-slave endoscopic surgical robot [2] to ensure practicality and repeatability of the experiments. Note that the experiment was conducted with fixed TSM configuration. The cumulative angle of sheath configuration was kept at 3π . Furthermore, we made sure that the sheath did not buckle throughout the experiment so that the data we collect was consistent.

Figure 19 Schematics of experimental test bed

Figure 20 Experimental set-up

3.4 DATA ANALYSIS

The measurements made in this experiment were processed by a QPIDe data acquisition board in real-time. Readings of the load cells are filtered using a second-order low pass filter with cut-off frequency of 150 rad/s and damping ratio of 1. Normalizations is applied to both training and testing sets in order to improve the learning efficiency of the neural network. The

mean μ_{train} and variance σ_{train}^2 were obtained from the training input data $d_{prox}, F_{prox} >$.

The magnitudes of the motor's cycling motion ranged from 5° to 50° with an increment of 2.5° (diameter of the pulley is 26mm), and the tendon was kept at a constant speed (2 mm/s) with closed-loop position control. This speed is normal for tendon-driven endoscopic surgical robots, and the incremental motion magnitude ensured a wide spectrum of proximal motion and force. One set was randomly chosen to be the test data set, two sets were randomly chosen to be the development data sets, the remaining twenty sets were concatenated stochastically with `randperm()` in MATLAB, and were then used to train the deep neural network models. As for the LSTM training, we used $20 \times 200s = 4000s$ of training data with random concatenation. The length of each training data collection could be more than 200s or less than 200s in actual cases. In our case, 200s is a reasonable duration for the specified motion pattern, as it allows force responses of motor motion ranging from 5° to 50° to be recorded multiple times and thus ensures a diverse and robust data collection. We collected 23 sets of 200s tissue data so that 2 sets can be randomly selected from them to be the development sets and one as the testing set (All testing sets in this study were taken to be 200s). During the LSTM training, the algorithm would divide the whole 4000s of data into several batches, and feed them in simultaneously. Therefore, the length of each training data set before concatenation does not affect the overall training result. In this study, we maintained consistent 200s of testing data, so when comparing result performance, there was no bias introduced from the time duration. However, in practice, the prediction output from the proposed LSTM model can be of any time length.

3.5 PHASE I: CONSTANT SPEED, KNOWN SHEATH CONFIGURATION

As mentioned previously, the tests aimed to simulate and compare the performance of two types of deep neural networks regarding their prediction accuracy and abilities to generalize the hysteresis profile of TSMs. In this section, MLP and RNN-LSTM were examined experimentally using identical training, testing and development data sets. Together their results were compared with those of the mathematical modelling approach conventionally used in the literature. After that, the better ANN was further investigated in its repercussion caused by using a reduced lessened training data set and the possibility of applying transfer learning.

3.5.1 Performance of LSTM, MLP, and Modelling

Table 1 Prediction performance

	Number of hidden layers	Number of neurons in each layer	Activation function	RMSE
LSTM	4	65	Tanh	0.0219 N
MLP	4	100	ReLU	0.1160 N
Modelling	N.A			0.4729 N

Both MLP and RNN-LSTM were built in deep models and their final architectures used in this study are listed in Table 1. A development set was used in this case to tune the hyper-parameters of ANNs so that the information in the test set does not infiltrate into the tuning process. Since finding the optimal architectures for ANNs is still open research, the author followed the rule of thumb to choose the hyper-parameters [132, 133]. The following range of tuning is explored for this particular problem scale: 2 to 5 for the number of layers and 50

to 150 for the number of neurons in the hidden layers. It was found that with an architecture deeper than 5 layers the algorithm may not converge. In addition, any number of neurons that is more than 150 does not significantly improve the learning accuracy. The ANNs were trained with 0.001 learning rate for 1000 epochs using Adam optimizer [134]. All the weights in the hidden layers were randomly initialized using Glorot uniform distribution. In addition, 5% dropout was applied to both ANNs during training to prevent overfitting.

Figure 21 Prediction results and hysteresis profile

(a) Prediction results (for a clear view, only three cycles are plotted); (b) predicted hysteresis profiles

RMSE was calculated using $\langle F_{\text{dist}} \rangle$ from distal load cell readings and $\langle \hat{F}_{\text{dist}} \rangle$ produced by corresponding methods over the 200s test data set. Both ANNs were found to

produce good tracking and smaller RMSE than using the mathematical modelling approach. For a clear view, only three cycles were plotted in Figure.24 (a) to illustrate how well the prediction signals reflect the distal force of TSM. All three methods were able to depict the overall pattern, yet it has to be highlighted that LSTM has the best agreement with the actual load cell readings. In addition, as shown in Figure.24 (b) hysteresis profile, LSTM and the modelling approach captured more precisely the detail of the transition phase than MLP. It has come to our attention that since the modelling approach applied different equations for different hysteresis phases there were discontinuities in between transition phases and releasing phases as shown in the zoom-in view of Figure.25. In comparison, hysteresis profiles learnt by the two ANNs approaches demonstrated full continuity throughout the entire prediction process. Our experiment results showed that LSTM performed outstandingly in both prediction accuracy and learning of the actual hysteresis profile.

Figure 22 Zoom-in of one ANN prediction peak

Figure 23 Zoom-in of the modelling approach discontinuity between transition phase and releasing phase

The transition phase is crucial to the force prediction process as it usually contains the local maximal force. It was clear that both ANNs made excellent predictions in the pulling and releasing phases. However, the discrepancy in their RMSE mainly came from how the two ANNs handle the transition phase. In the Figure.26 zoom-in plot, the MLP prediction signal oscillated and tended to overpredict in the transition phase. This result agreed with their learnt hysteresis profile that we observed in Figure.24 (b). The prediction of MLP in the transition phase failed to generalize to a consistent pattern, thus, further strengthened the above verdict of the inability of MLP to handle the transition phase signal.

Our study provided insight into how the fundamental difference between MLP and LSTM affected their performance when dealing with time series sequential data. Most importantly, when a prediction was made on one time step, MLP considered inputs of the current time step only whereas LSTM's recurrent structure allowed it to make use of not only the information of the current time step, but also the information in all previous time steps.

The cell state $C^{(t)}$ contains a long-term memory of how the pattern of data would change in accordance with the current input and previous outputs. LSTM firstly identified the hysteresis phase at the present time step, and then with the help of 3 gates regulating information flow accordingly, a good prediction was made that fulfilled the actual force hysteresis profile. It was technically difficult for MLP to do the same because by considering the inputs of the only current time step, there was not enough information to realistically identify the current force hysteresis phase. As a result, a feedforward net, like MLP, would process the input sensory data from different hysteresis phases in the same manner. Moreover, as aforementioned in Section 2.1 Tendon-Sheath Mechanism, the friction loss between the F_{prox} and F_{dist} during the transition phase depends on the previous history of displacement. Therefore, the memory mechanism of LSTM was critical in this case to learn and generalize the distal force behaviours during the transition phase.

3.5.2 Further Investigation in Training Data

Our results provided compelling evidence that the proposed LSTM approach is fully competent of learning the force hysteresis model of TSMs. On the other hand, acquiring training data from 20 pieces of tissue for LSTM was feasible but time-consuming. A further experiment was carried out to test the ability of LSTM's to learn based on data generated from only one tissue and generalize on other tissues.

Figure 24 LSTM force prediction

Figure 25 LSTM hysteresis profile

Figure.27 presents the results of LSTM trained with data generated from one random tissue and predicted on the benchmark tissue. Prediction RMSE was 0.1072 N. Identical experiments were carried out on three other pairs of different tissues. Similar prediction performance was obtained with an average RMSE of 0.1364 N. It was clear that LSTM still managed to produce a decent prediction accuracy using the simplified training data set while learning the correct force hysteresis profile in different phases.

We observed that if an LSTM model trained with the data generated from one tissue were used to make predictions on the same training tissue, i.e., the training data set was identical to the testing data set, the average prediction performance was $\text{RMSE} = 0.0539 \text{ N}$. The prediction accuracy was distinctly good. However, it wasn't as good as the LSTM trained with 20 different tissue ($\text{RMSE} = 0.0219 \text{ N}$). Besides, unlike the former, training data set for 20-tissue-LSTM model didn't contain the testing data set which makes it a more difficult problem setup.

To sum up, training an LSTM model using a diversified training data set is crucial for making accurate predictions. Nevertheless, LSTM is capable of learning the actual force hysteresis profile from lesser training data and making a moderately good prediction

3.5.3 Transfer Learning

Transfer learning is a technique in machine learning that focuses on storing knowledge learned from source task (TSM with a spring as payload) and applying it to a different but related target task (TSM with stomach tissue as payload). Such an approach brings benefits such as avoiding extensive data acquiring efforts.

Figure 26 Transfer Learning force prediction

Figure 27 Transfer Learning hysteresis profile

To explore the possibility of applying transfer learning, another effort was made to train an LSTM model using data generated from manipulating a spring at the distal-end and then make predictions on the benchmark tissue. The stiffness of the spring and benchmark tissue was measured as 18.89 N/m and 4.80 N/m, respectively. Note that the stiffness of the spring and the tissue was not similar. However, this does not prevent LSTM from learning the relationship between proximal and distal force in the given TSM.

Prediction results showed that the model learnt from manipulating a spring (ST) can be successfully transferred to make distal force predictions on tissue manipulation (TT). Figure.29 shows that the overall pattern (low-level feature) was well predicted. However, RMSE of 0.1838 N was measured, and there was obvious error in the rear pulling and releasing phase. Namely, the response when the payload tension was high and when the payload was relaxing back to its non-tensioned form. In both cases, the tissue's viscoelasticity was proved to bring a difference to the high-level features of force response.

We conclude that LSTM could make satisfactory predictions on tissue force response by learning from force response of a spring. However, it was difficult to eliminate the prediction error completely due to the intrinsic disparity between the tissue and spring's viscoelastic property. The force response difference caused by such disparity was easily reflected on the distal load cell, as high-level features, but not so easily on the proximal load cell because of the friction loss in TSM. As a result, during transfer learning, LSTM was only trained with the high-level features of spring force response but not from those of the tissue. Note that the current accuracy of transfer learning does not surpass the accuracy of the mathematical modelling approach. However, the author believe that this could be a promising direction for further study so that we can achieve a short data collection procedure and good prediction accuracy. Possible approaches to tackle the problem with the lack of high-level features are discussed in Section 5 future work.

3.6 PHASE II: VARYING SPEED, KNOWN SHEATH CONFIGURATION

In this part of the research, the necessity of considering the impact of training tendon movement, including velocity and trajectories, was further investigated. First of all, an experiment was conducted to examine force hysteresis profiles of the same TSM setup operating under different system speeds.

The normal system velocity of the tendon-driven NOTES robot ranges from 0.5 mm/s to 10 mm/s. Figure. 31 reveals the five force hysteresis profiles of a TSM operating under an identical tendon displacement but different system operation speed. It was observed that the increment of velocity brought two distinct effects to the hysteresis profile: 1. gentler slope in the pulling phase and steeper slope in the releasing phase; 2. decrease in the distal force in the transition phase. It was also observed that the bigger the difference in velocity the more obvious the above effects. It was clear that varying velocity affects the force hysteresis profiles of TSM yet the magnitude of the impact on the performance of the deep LSTM model remains unknown.

Therefore, another experiment was designed to study how much would the varying velocity affect the performance of deep LSTM in distal force prediction tasks.

Figure 28 Hysteresis profile under various velocities

3.6.1 The Impact of Varying System Velocity

To test the impact of varying velocity, an LSTM was trained using data sets generated under a system velocity of 2 mm/s. The trained LSTM model was then used to make predictions on 5 different test data sets with velocities of 0.5 mm/s, 1 mm/s, 2 mm/s, 5 mm/s, and 10 mm/s, individually. Note that the tendon movements for all data sets collected shared identical trajectories. The only difference lies in their system velocities. In addition, a spring (stiffness 18.89 N/m) was used for the experiments as payload at the distal end. The goal is to control the variables so that the response of the payload does not introduce variance.

Figure.32 plots the force hysteresis profile prediction results of the LSTM on test sets of varying velocities. Figure.32 (c) shows good prediction accuracy since the test velocity is the same as the training velocity. Evidentially, smaller system velocities, shown in Figure.32

(a-b), demonstrated similar prediction patterns and so did the ones with larger system velocities, shown in Figure.32 (d-e). Furthermore, as we compared Figure.32 (a-b) to Figure.32 (d-e), it could be observed that increased and decreased system velocities resulted in different types of error patterns. Error magnitude increases with the difference of velocity between training and testing. RMSEs for data sets plotted in Figure.32 (a-e) are 0.4552 N, 0.3454 N, 0.0469 N, 0.5704N and 1.4920 N, respectively. The influence of velocity on LSTM's prediction accuracy was clear.

Figure 29 Force predictions on five velocities

3.6.2 The Impact of Varying System Velocity

Inspired by experiments in 4.2.1, it came to our attention that the trajectories of tendon movement could also be a variable that affects LSTM's learning. To test the impact of varying trajectories, an LSTM was trained using data sets generated from constant speed (2 mm/s) motor trajectories, shown in Figure.33 (a), and predicted on test data set generated from sine wave motor trajectories, shown in Figure.33 (b). The experiment was designed in a way that the sine wave trajectories speed is close to 2 mm/s when pulling and releasing.

Figure 30 Training and testing trajectories

Figure 31 Force prediction over different trajectories

As shown in Figure.34, for LSTM prediction, it was observed that there was over-prediction in the higher peaks (average peak error magnitude of 40.7%) and under-prediction in the lower peaks (average peak error magnitude of 39.4%). In the peaks of each cycles, the difference in trajectories is bigger, and the trained LSTM made more significant prediction error than it would during the range of pulling and releasing phase. Mathematical modelling approach was also applied to the test data set and its prediction is shown together in Figure.34. The RMSEs for LSTM and modelling approach predictions were 0.7512 N and 0.6136 N, respectively. Clearly, the trajectories needed to be improved so as to train a more versatile LSTM model.

The experiment results in 4.2.1 and 4.2.2 have surfaced the incompleteness of training data generation if the impact of system velocity and trajectories was not taken into account. In addition, we concluded that it was necessary to consider the varying velocity when designing training data generation for LSTM and we should use $\langle d_{prox}, F_{prox}, v_{prox} \rangle$ as input instead of $\langle d_{prox}, F_{prox} \rangle$.

3.6.3 Training with Non-periodic Motor Movement

In order to train an LSTM model to make good predictions on a system with varying velocity and trajectories, a more versatile training strategy was proposed to incorporate the computer-generated, non-periodic motor movement, shown in Figure.35 (a). The input of LSTM was set as $\langle d_{prox}, F_{prox}, v_{prox} \rangle$ so that the neural network can learn and generalize the relationship between system velocity and force hysteresis profile during training. As presented in Figure.35 (b) and Figure.35 (b), the problem setup became harder as there were occasions when the proximal load cell encountered significant fluctuations in force yet the distal force remained almost constant. The force hysteresis profile no longer follows the

pulling-transition-releasing pattern in sequence, and can sometimes reverse back to the pulling phase from the transition phase. Therefore, identifying the correct hysteresis phase is paramount. This phenomenon was mainly caused by the irregular movement of the TSM and occurred mostly during the prolonged transition phase.

Figure 32 Movement and tension in TSM

Figure 33 Force prediction and hysteresis profile of new strategy

To examine the proposed strategy, twenty-three pieces of tissue were used to generate experimental data. Three of them were randomly chosen to be the testing data sets, and the remaining twenty pieces were used as the training data sets. Figure.36 shows the prediction performance and hysteresis profile learnt by LSTM. The best prediction accuracy among the three testing data sets has an RMSE of 0.0917 N, and the average RMSE is 0.0975 N. Note

that the overall prediction was in good agreement with the actual load cell readings yet not as good as the prediction done on the constant velocity experiment set-up. Specifically, the biggest prediction error was mainly introduced from two regions:

- Higher peaks: max error occurred when error magnitude = 0.42 N and error = 3.2%
- Lower peaks: max error occurred when error magnitude = 0.21 N and error = 4.5%

From Figure.36 (b) hysteresis profile, we found that LSTM was capable of adapting to different pulling phase and releasing phase slope angles when the TSM was operating under various system velocities. In addition, the critical points where the system switches into transition phases were accurately located. However, small discrepancies were found in the prediction for the transition phase.

To sum up, LSTM gave good predictions on identifying the correct hysteresis phase that the system was in and the overall performance was improved when taking into account the velocity during the training data collection.

3.6.4 Predictions on Manual Manipulation

During the actual operation of robotic-assisted NOTES, the motor movement is not as smooth as computer-generated trajectories. The irregular movement trajectories and the jerkiness of human hand manipulation must be considered. The last experiment in this study was done to examine how well the model trained in Section 3.6.3 would perform on a more realistic case when the tissue was manipulated under a manually controlled motor movement through TSM. The manual control signal is generated by operating an Omega.7 haptic device (Force Dimension, Switzerland), mimicking the motion trajectory and velocity in real surgical operations. The prediction performance is depicted in Figure.34.

Two considerations are important in this experiment: the algorithm's overall ability to trace the distal-end force (reflected by RMSE) and the ability to preventing catastrophic surgical accident (reflected by the maximum error). The maximum force of a robotic manipulator should be kept below 50N (we tested our instrument requires 70N to tear intestine tissue) to prevent any unintended tear and knowing the maximum error helps us to monitor and maintain the surgical instruments in the safe operating range. It was clear that we can apply the LSTM model trained with computer generated training data sets and make reasonable predictions on human hand manipulation on the real tissue. RMSE of the prediction was 0.2287 N with the maximum error of 0.81 N.

In this study, manual manipulation data was not used as training data sets for LSTM. This is because the data generation process could be time-consuming and tedious for end users to conduct. The strategy proposed in Section 3.6.3 could produce decent prediction accuracy, so it would be the preferred approach for its simplicity.

Figure 34 Force prediction on hand manipulation

3.6.5 Training and testing time

The time needed for data collection on twenty tissues during real-life use is around 3 hours. Training an LSTM model based on the above training data using the architecture described in this study requires 4 to 5 hours. During NOTES operation using our robotic system, the sensory data are processed by two Quanser QPIDE boards with a refresh rate of 1000 Hz, namely, producing one input set every 0.001 s. For the LSTM model, the average time taken to make one prediction is 0.00075 s for a single time step which is adequate for real-time use. This information was measured with our validation experimental set-up. Our PC configuration was as follows: Processor-Intel(R) Xeon(R) CPU E5-1650 v3 @ 3.5GHz, RAM-32.0 GB, GPU-NVIDIA Quadro K2200.

Chapter 4: Research Design and Experimental

Results for Unknown Configuration

This chapter presents the design adopted by this research to achieve the objectives stated in Section 1.3 of Chapter 1: acquiring sheath cumulative angle information and time-series force prediction based on accessible sensory data from the proximal-end of a robotic NOTES system. Section 4.1 presents important understandings of TSM in surgical robot and different component of the robot that we used for this particular study ; Section 4.2 details the different phases of experiment in which the methodologies were implemented, and the signal processing involved for each technique; Section 4.3 describes the force prediction strategies used in two steps of the experiment including prediction of the cumulative angle within the TSM as well as model selection for time-series data prediction. The main challenges facing this research are two folds: firstly, making sure the approach is robust when encountering unseen configuration or a cumulative angle that is not within the training dataset. Secondly, develop a method to collect distal data for ground-truth training label without compromising the actual operation of the surgical robot. For example, the movement and force hysteresis profile of the instrument should not be different when collecting the distal data.

4.1 THE FLEXIBLE ENDOSCOPIC ROBOTIC PLATFORM

4.1.1 Tendon-sheath Mechanism in Endoscopic Surgical Robot

Tendon-sheath mechanisms (TSMs) are commonly used for force transmission in systems with long and tortuous structures such as NOTES and soft wearable robotic systems [135] when the application demand for a compact system solution. As shown in Figure. 38(a), TSM has two main components: an actuation cable (tendon) that transmits force and movement, and a hollow coil (sheath) that wraps around the tendon. TSM offers several advantages including lightweight, compactness, high payload transmission capability and low cost. However, TSM is intrinsically associated with nonlinear friction between the tendon and sheath that causes backlash, hysteresis, and tension loss from the proximal-end force to the distal-end force, which is defined as $f_{TSM} = F_{prox} - F_{dist}$. The relationship between F_{prox} and F_{dist} is often depicted to characterize the unique properties of TSMs, also known as the force hysteresis profile, as illustrated in Figure. 38(b). There are three distinct phases: the pulling phase (phase ①, where the proximal motor winds in and f_{TSM} increases), the releasing phase (phase ②, where the proximal motor unwinds and the tendon relaxes back to its non-tensioned state) and the transition phase (phase ③, where f_{TSM} changes its direction and the system operates in the vicinity of zero velocity). In the transition phase, F_{prox} could change drastically while the F_{dist} remains almost constant, which is commonly referred to as the deadzone. Therefore, it is crucial to identify the correct force hysteresis phase during a force estimation task as F_{prox} and F_{dist} exhibit different relationships in the three phases. In addition, Figure. 38(c) shows how the friction loss changes in different hysteresis phases. Phee et al. [136] analyzed the mechanics of TSMs by describing the nonlinear relationship of F_{prox} and

Figure 38 TSM demonstration and hysteresis profile

(a) TSMs are commonly used in NOTES robots for force transmission. A demonstration of TSM structure is shown where the proximal-end (on the left) is connected to the actuation housing and the distal-end (on the right) is connected to the robotic end-effector (b) TSM force hysteresis profile is depicted. There are three phases (①-③) where the F_{prox} (x-axis) and F_{dist} (y-axis) exhibit different relationships (c) A TSM friction profile that describes the relationship between the friction force and motor movement.

F_{dist} in the three hysteresis phases. Later, Wang et al. [137, 138] improved and generalized the model, and the representation is summarized in Equation (1-3):

$$F_{dist,\varphi} = F_{prox}e^{-\mu\varphi\xi} \quad (1)$$

$$F_{dist,tran} = F_{dist,pull,last} \quad (2)$$

$$F_{prox,tran,last} = F_{prox,tran,start}e^{-2\mu\varphi} \quad (3)$$

Where ξ denotes the direction of relative movement of the tendon to its associated sheath and μ is the friction coefficient between them. Equation (1) describes the relationship of $F_{dist,\varphi}$, the distal-end tendon force, and F_{prox} , the proximal-end tendon force during the pulling phase. Equation (2) shows that $F_{dist,tran}$, the distal-end force during transition phase stays constant and has the value of the distal-end force at the end of the pulling phase, denoted as $F_{dist,pull,last}$. $F_{prox,tran,start}$, $F_{prox,tran,last}$ represent proximal force at the start and end of the ③ transition phase as shown in Figure.38(b). φ is the cumulative bending angle in the sheath configuration.

The important conclusion from these studies is that for a given set of tendon and sheath, $F_{dist,\varphi}$ could exhibit different relationships with $F_{prox,\varphi}$ depending on the system sheath configuration. More specifically, according to Equation (1) and (3), the relationship between $F_{dist,\varphi}$ and $F_{prox,\varphi}$ primarily depends on the system cumulative bending angle φ . Figure.39 (a) presents three different force hysteresis profiles measured on the same NOTES robot when the cumulative bending angles are 100°, 250° and 400°, respectively. Under an identical actuation movement, higher degree bending angle configuration exhibits a slower slope in the pulling phase ① and lower $F_{dist,\varphi}$ in transition phase ③. This is because as the TSM path become more tortuous, there will be an increasing friction loss between the proximal and distal ends.

Figure 39 Hysteresis profiles at various cumulative bending angles

(a) TSM system exhibits different force hysteresis profiles for different cumulative bending angles. Three hysteresis profiles are plotted for three cumulative bending angles with identical system movement on the same TSM. (b) The corresponding TSM friction profiles are plotted for the three bending angles.

4.1.2 Experimental Setup

This paper proposes an approach to estimating the distal-end force of TSMs for NOTES robots. To ensure the practicality and reproducibility of the experiment, we validated this method by using a flexible endoscopic surgical robot that has passed a live animal study [139]. Figure.40 (a) shows the essential components of the surgical robot used in this study. The robot features a grasper with three Degrees of Freedom (DOF) (yaw, pitch and gripping) driven by three pairs of TSMs, separately. The tendons are connected back to the actuation housing and are driven by DC motors (2657W024CR from Faulhaber Schonaih®) and the proximal movements are measured with encoders (HEDS-5540 A14, 500CPR) attached on each motor including displacement and velocity of the tendon d_{prox}, v_{prox} . The sheaths of the tendons are stopped at the entrance of actuation housing by their corresponding load cells (FUTEK LTH300) which are used in this experiment to measure the compression force at the proximal-end of the TSMs. It was proven by Lai et al. [140] that in a TSM, at any given location along the path, the tension in the tendon is equal to the compression force in the sheath. Therefore, the load cells reflect the actual proximal-end tension in each tendon. This robot employs two motors to maintain the bidirectional motion of each DOF. Hence, when one motor (active motor) winds in, its counterpart (passive motor) unwinds to release the tension on the passive tendon. Six load cells are embedded in the actuation housing to record $F_{prox,1}$ to $F_{prox,6}$, respectively, during the operation. We used 0.5 mm diameter tendon together with 1.14 mm outer diameter sheath both from Asahi Intecc® for movement transmission. The movements are controlled by PID controllers and all sensory data was acquired and synchronized by MATLAB SIMULINK interfaced with QPIDe data acquisition board from Quanser Quarc®. Sampling rate is set to 1000 Hz for sensor readings and analog output processing, which is sufficient for this experiment and real-world operations. 3D printed barriers are fixed on the supporting acrylic board by screws, which are used to

Figure 40 Experimental platform

- (a) This study is validated on an actual TSM-driven flexible NOTES robot. The key components of the experimental set-up are depicted. Sensors, motors and drivers are shown on the left side. The flexible robotic arm is placed on a testbed as shown on the right side.
- (b) A demonstration of the TSM path of the surgical robot. The bending angle is cumulated from point A to point B through segments ①-⑤.

constraint the configuration of TSM. The cumulative bending angle φ is calculated from

point A (this is where the robotic arm goes into the endoscope during the surgical operation) to point B: end-effector. For instance, as demonstrated in Figure.40 (b), the φ between ① and ② is 90° , and the φ between ② and ⑤ is 270° . Since the segments in between ② and ⑤ all curve in one direction, their bending angle is cumulated in one go. The path of the TSM is organized in a way that is similar to the route configuration of the gastrointestinal tract. When designing the configuration, we need to be aware of differences of the gastrointestinal tract of different individual as well as the depth we insert the instrument. Both factors will affect the path of the TSM and this factor will be further examined and discussed in Chapter 4.5.

4.1.3 Working Principle and Integration Method of the FBG-based Sensor

Although the approach proposed in this paper does not require additional sensors during operation, it is crucial to have accurate distal-end force measurements for supervised learning during the training phase. Since the end-effector has an outside diameter of only 4.2mm, it is difficult to fit in conventional force sensors. Therefore, a Fiber Bragg Gratings (FBG) force sensor was used in this study to measure the distal forces to provide labelled training data for ANNs.

FBGs are generally photo inscribed in the silica core of a single mode optical fiber by using a UV laser beam through a phase mask [141]. FBG reflects a specific wavelength of light called Bragg wavelength λ_B , which shifts with respect to the changes in temperature and strain, as shown in the Equation (4) [142].

$$\Delta\lambda_B = (K_T\Delta T + K_\varepsilon\Delta\varepsilon)\lambda_B \quad (4)$$

where ΔT , $\Delta\varepsilon$, K_T , and K_ε are the changes in temperature, axial strain along the fiber, thermal sensing coefficient, and strain sensing coefficient of the fiber material, respectively. In this

study, to minimize the temperature cross-sensitivity, all the sensing experiments were executed at a room temperature of $24.5\text{ }^{\circ}\text{C} \pm 0.2^{\circ}\text{C}$.

Figure 41 FBG sensors

(a) An FBG-based force sensor is used to measure the distal-end force of the TSM-driven NOTES robot. The working principle of the FBG-based force sensor is shown. At any given point along the path, the tension in the tendon has the same magnitude of the compression force in the sheath. (b) A schematic of the robotic grasper integrated with a FBG-based force sensor. (c) A photo of the robotic grasper with the force sensor.

The FBG-based force sensor¹ [137] was mounted at the distal-end of a TSM in the robot, as shown in Figure.41 (a-c). The sensor is FBG fiber attached on a nitinol tube welded on a sheath, and it is located at the closing-jaw TSM of the grasper. When closing jaw action is

¹ A Singapore provisional patent (10201804332S) has been filed on this force sensor.

executed, the associated tendon is pulled at the proximal end by the active motor, and simultaneously the sheath experiences compression, which is then transmitted to the force sensor on the sheath. It was proven that at any cross-section (labelled as 1 to 4), the tension T on the tendon and the compression force C on the sheath have a relationship of $T = -C$. Thus, the FBG sensor captures the strain changes of the nitinol tube due to this compression, and the corresponding wavelength shift reflects the distal-end tension. A prototype of the end-effector with a transparent outer tube is illustrated in Figure.41(c) to visualize the actual mounting of the force sensor. To fabricate this force sensor, a 1mm-grating FBG sensor (Technica, USA) is bonded with a 3mm-long nitinol tube using epoxy, and this tube is welded in between two sheaths, where the distal sheath has a short length of 3cm. The force sensor has a sensitivity of 33.09pm/N with a Root-Mean-Square-Error (RMSE) of 8.50pm, which indicates a measurement error of 0.26N. In this work, wavelength data was collected in real time through an optical sensing interrogator (Micron Optics si255, USA), with a scan rate of 1000 Hz.

4.2 METHODOLOGY

4.2.1 Recurrence Plot

Recurrence plot (RP) is a graphical tool devised to compute dynamic parameters from time series. It was initially proposed by Eckmann et al. to visualize the periodic nature of a trajectory through phase space [143]. RP is used for a wide variety of time-series data tasks such as sound analysis, human activity analysis and plant species recognition [144, 145]. In other words, RP allows us to convert the multi-dimensional phase space trajectory to a 2-dimensional representation for further analysis purposes. In this study, to reconstruct the phase space, we used an autocorrelation function to find a suitable time delay τ . In addition, false nearest neighbours method [146] is applied to estimate the optimal number of embedding dimension m . The general recurrence plot is defined by:

$$R_{ij} = \Theta\left(\epsilon_i - \|x_i - x_j\|_2\right), \quad x_i \in \mathcal{R}^m, \quad i, j = 1 \dots N \quad (5)$$

where $\Theta(\cdot)$ is the Heaviside function, ϵ_i is the threshold distance, $\|\cdot\|_2$ represents the Euclidean norm, and m is the embedding dimension for N number of considered states x_i . In our case, x is the state vectors of load cell time-series data, i.e., the reading of the corresponding load cell. For the robotic grasper, each DOF is driven by two tendons, and each tendon has one load cell at its proximal end. Figure.42 (a) shows the readings of the two load cells of the two tendons controlling the gripping DOF, i.e., the system response, during the probing process (details described in Section 3.4.1). Note that one signal always decreases when the other increases. This is because the active tendon will experience increasing tension while the passive tendon's tension decreases. Two versions of recurrence plots are constructed for these two particular time series (or load cell readings). Parameter identifications for embedding dimension and time delay are further discussed in the later sections. Figure.42 (b) is the unthresholded RPs while Figure.42 (c) is the thresholded RPs

Figure 42 Probing signal and recurrence plot

(a) The proximal-end forces of the two tendons that drives the closing jaw of the robotic grasper for a specified motion command. Two load cells, referred to as channel 1 and channel 2, are embedded in the proximal end motor housing for the closing-jaw DOF. (b) The two load cell readings are converted to unthresholded RPs with channel 1 on the top and channel 2 on the bottom. (c) The two load cell readings are converted to thresholded RPs with channel 1 on the top and channel 2 on the bottom.

with $\epsilon_i = 0.5$ (we have normalized the array to in between 0 and 1). In this study, as we aim to retain the most texture and color information for the ANN to learn, we have adopted the unthresholded RP approach which is defined by Equation (6):

$$R_{i,j} = \|x_i - x_j\|_2, \quad x_i \in \mathcal{R}^m, \quad i, j = 1 \dots N \quad (6)$$

Figure 43 CNN and LSTM for force prediction

(a) CNN is used in the proposed approach for classification. It takes unthresholded RPs as input and computes a 13-dimensional vector of softmax scores as output. (b) LSTM is used for force prediction. Proximal sensory data is fed into LSTM after preprocessing, and the prediction is produced in the form of distal forces. 150Hz is chosen where the trade-off between load cell noise and preprocessing delay is balanced.

Through a series of convolution and pooling operations, CNN is capable of extracting spatial features from different positions of the input which, for most cases, proves to have a more robust performance as compared to manually engineering features for classification tasks. Fig. 43(a) demonstrates the architecture of CNN used in this study. The network takes a pair of RPs as input and computes output in the form of a vector of softmax scores.

4.3 FORCE ESTIMATION STRATEGY

In order to make an accurate distal-end force prediction in robotic-assisted NOTES system, we propose a two-stage strategy. In stage one, the goal is to estimate the current cumulative bending angle of the system through CNN classification and then select two best performing LSTM models, accordingly. In stage two, the selected models are then used to make force predictions during actual system operation.

Before arriving at the above solution, we actually have experimented with 3 other solutions including: 1. One-phased solution of directly using LSTM for distal-end force prediction. 2. Two-phased solution of RNN for angle classification followed by the LSTM distal-end force prediction. 3. Two-phased solution of using Recurrent CNN for angle classification followed by the LSTM distal-end force prediction. The first approach has poor performance since the configuration change was not taken into account. The second and the third approach lack precision mainly in the first phase. This is because small configuration changes bring very subtle change to the feedback in the 'time space'. However, these changes can be more easily observed in the 'phase space' as reflected in the colour intensity when capturing using recurrence plots. Therefore, we use recurrence plot to pre-process the feedback signals into 'phase space' and apply a CNN for configuration classification.

4.3.1 Stage One

Figure 44 Stage one flowchart

(a) A flowchart of the Stage one pipeline. Two LSTM models are selected after the NOTES robotic system initialization. (b) A probing signal is used in Stage one system initialization with a duration of 10s.

As depicted in the flowchart in Figure.44 (a), the robotic system is initialized with 2N pre-tension on each individual tendon. Next, a probing signal was sent to the gripping DOF of the end-effector. Figure.44 (b) describes the probing signal which is essentially the movement reference for the motors driving the gripping DOF. Various types of probing signals were examined in this study, and we found that a signal with a changing velocity and local maximal amplitude tends to produce a good performance. The probing process lasts for 10 s. In the meantime, the proximal forces on the two TSMs of the gripping DOF were recorded by the corresponding proximal load cells as raw data. The data was filtered and normalized, and then constructed into recurrence plots. Next, the recurrence plots are sent to a CNN classifier after being resized to 256×256 pixels. The CNN classifier assigns a softmax score, as described in Equation (7), to each categorical class which represents the probability of the current system cumulative bending angle being a certain angle. The normal range of cumulative bending angle in the NOTES procedure is within 90° to 450° . In this study, we consider 13 classes within this range. The bending angles are selected uniformly with 30°

interval, namely, $\{90^\circ, 120^\circ, 150^\circ, \dots, 390^\circ, 420^\circ, 450^\circ\}$. In other words, the classifier receives RPs and computes an output in the form of a vector which contains 13 softmax scores corresponding to the above 13 classes.

$$P(Y = k|X = x_i) = \frac{e^{s_k}}{\sum_{j=90^\circ}^{450^\circ} e^{s_j}} \quad \text{where } s = f_{CNN}(x_i; \theta) \quad (7)$$

Equation (7) is the standard softmax function used in this study that computes the probability of the current bending angle being k when CNN is given the RP input x_i , for $k = 90^\circ, \dots, 450^\circ$ and θ represents the weights in CNN after training. On the other hand, we have trained 13 LSTM models for each predefined bending angle used for the force prediction in stage two. Two LSTM models with the highest softmax scores are selected correspondingly. The details of LSTM models will be introduced in Section 4.3.2 Stage two.

All training data for this study are collected from the actual flexible NOTES robot. For CNN, we have collected 30 sets of data for each of the 13 classes of bending angles. There are slight state variations for each run of the system due to factors such as initialization and instrumental deviations. We found that 30 sets of data are sufficient for the CNN model to learn and generalize over these differences. As introduced in Section 2.2, we have two load cells attached to each DOF, thus the raw data is recorded in two channels $\langle F_{prox,1}, F_{prox,2} \rangle$ when probing signal is sent. The data is filtered with a second-order low pass filter and normalized using the mean and variance of each individual channel. After rescaling, the data is used for the CNN training as constructed recurrence plots in the shape of $(256, 256, 2)$, where 2 represents the number of channels.

In supervised learning, the training dataset needs to be labelled. Instead of labelling the 13 classes using vanilla One-Hot-Encoding (OHE) technique [147], which is the most prevalent strategy for labelling CNN classification training data, we applied a modified version of OHE. By using conventional OHE, we would be assigning 1 to the true class label and 0 for all

other classes. Alternatively, we assigned 0.9 to the true class label and diffused 0.05 to its two neighbouring classes. This technique allows the classifier to establish an understanding of the consecutiveness of the 13 classes while still preserve the dominance of the true label. The benefit of doing so is that the CNN model will perceive the bending angles as more of ordinal categorical labels instead of nominal categorical labels, as what we usually do with image classifications. For instance, the bending angle 180° class is labelled as (0, 0, 0.05, 0.9, 0.05, 0, 0, 0, 0, 0, 0, 0). Another way to achieve this purpose is to build the CNN model as a regression model and label the training data by using the actual bending angles directly. The reason that we have adopted the first approach will be further discussed with experimental results in Chapter 4.6.

Figure 45 Stage two flowchart

(a) A flowchart of the Stage two pipeline. Distal forces are estimated by the two LSTM models (selected in stage one) based on the proximal sensory readings of the robotic system during operation. (b) A sample of 300s of non-periodical movement reference for training data collection.

4.3.2 Stage Two

In stage two, we deploy the two LSTM models selected in the previous stage and use their corresponding softmax scores as weights to make combined predictions of the distal forces of the TMS. During system operation, the proximal sensors on the surgical robot provide inputs for the LSTM models including displacement, velocity, and proximal forces on the two associated tendons. These sensory data are filtered and normalized before being sent to the two LSTM models. Finally, we take a weighted average of the predictions from the two LSTM based on their previous softmax scores, as described in Equation (8):

$$LSTM_{final} = \frac{P_{k_1} LSTM_{k_1} + P_{k_2} LSTM_{k_2}}{P_{k_1} + P_{k_2}} \quad (8)$$

where $P_{k_1} = P(Y = k_1 | X = x_i)$; $P_{k_2} = P(Y = k_2 | X = x_i)$, k_1 and k_2 are the two bending angle classes with the highest scores, while $LSTM_{k_1}$ and $LSTM_{k_2}$ are the model predictions, correspondingly.

The training data for LSTM is collected by proximal sensors in the NOTES system as described in Section 2.2 in the form of $\langle d_{prox}, v_{prox}, F_{prox,1}, F_{prox,2} \rangle$. The label data for training is collected by using the FBG-based force sensor $F_{dist,target}$. For the actuation signal, we adopted the method which is a computer generated non-periodical movement in order to ensure the robustness of the trained LSTM models, as shown in Figure.45 (b). Training data volume of 1000 k time steps are used for each model. This process is repeated 13 times to build models for each individual bending angle class. Note that, in this approach, the FBG-based force sensor is only required during the training data collection. During the NOTES robot operation, the distal-end force sensor will be no longer needed.

In this approach, the proposed algorithm has only been trained with the 13 classes of cumulative bending angle that we have predefined. In reality, there are infinite possibilities of cumulative bending angle in the system. However, it is unrealistic to build an infinite

number of LSTM force prediction models. Furthermore, it was proven that, in TSMs, the force transmission is solely dependent on the system cumulative bending angle but not how the angle is distributed [26]. Therefore, we choose to build a limited number of LSTM models to cover the cumulative bending angle domain. In this study, we ultimately decide to cover the bending angle domain from 90° to 450° with 13 LSTM models by 30° uniform interval, which is referred to as resolution. As the resolution increases, we will have more accurate predictions. On the other hand, as the demand for resolution goes up, the time required for data collection and model training would also increase consequently. In the short, it's a trade-off between accuracy and time and training effort. The 30° uniform interval resolution achieves decent force prediction results which will be presented in Chapter 4.5 Stage two results.

4.3.3 Final strategy

Finally, we demonstrate the entire force prediction process for unknown TSM configuration with the help of the result from stage one and stage two.

As shown in Figure.46, a complete process goes as the following. Initially when the surgical robot is inserted into the human body during the operation, the cumulative angle is unknown to us. Once the surgical site is reached, the robot stop moving forward or backward. Hence we have a fixed TSM configuration for the rest of the procedure. We enter the stage one of the methodology: sending the probing signal to the robotic system and leverage the feedback signals to estimate the cumulative angle based on the proposed ANN architecture and recurrence plots. Secondly, 2 LSTM models are chosen based the softmax scores form phase 1 and will be used in the weighted force prediction. During actual operation, proximal force and displacement information is collected and fed to the aforementioned LSTMs to make real-time predictions.

4.4 STAGE ONE RESULTS

During the probing process, there are two load cells recording the response of the system's gripping DOF in the form of proximal-end tendon tension in channel 1 and channel 2, respectively. In order to find suitable embedding parameters for phase space reconstruction, we applied auto-correlation on each channel and identified the time delay τ . The optimal τ is identified as the distance between the centre peak and the first local minima. The embedding dimension, m , is the number of time delayed copies of the time-series signal used to track its trajectory in phase space. False Nearest Neighbours (FNN) method is applied in this case to determine the minimum number of embedding dimension required for these two channels. Therefore, we have $\{\tau=85, m=4\}$ for channel 1 and $\{\tau=55, m=5\}$ for channel 2 that minimize the average mutual information function [148] during the reconstruction of the recurrence plots in their corresponding channels. Note that channel 1 takes longer time delay for reconstruction and these embedding parameters are specific to the chosen probing signal.

Figure.47 visualizes the RPs that are sampled from different bending angles from the two channels. RPs from the same channel depict very similar texture due to the fact that they share the same actuation signal during the probing procedure. Therefore, they would have similar behaviours in their reconstructed phase space. Moreover, the intensity of the sub-regions demonstrates more distinct gradual differences across bending angle classes which allow the CNN model to effectively perform classification.

Figure 47 (a) In order to construct RPs, auto-correlation is used to determine time delay, τ . (b) FNN is used to determine embedding dimension, m .

Figure 48 (a) RPs sampled from load cell channel 1 across different cumulative bending angles. (b) RPs sampled from load cell channel 2 across different cumulative bending angles

As mentioned in the CNN training strategy, 30 training datasets are collected for each bending angle class. To evaluate the performance of the CNN model, we applied the five-

fold cross-validation (CV) protocol. The mean accuracy of the CV is 98.72 %. Finally, the CNN model is trained with all training data.

In order to validate the effectiveness of the proposed approach, we evaluated 4 different bending angles: 170°, 225°, 315°, and 400°. Table 1 shows the CNN prediction results:

Table 2 CNN bending angle predictions

	k_1 bending angle	k_1 softmax score	k_2 bending angle	k_2 softmax score
φ : 170°	150°	0.3440	180°	0.6162
φ : 225°	210°	0.4269	240°	0.5655
φ : 315°	300°	0.5335	330°	0.4458
φ : 400°	390°	0.6394	420°	0.2734

We tested bending angles that are not exactly the same with the training bending angles as this is what the algorithm is likely to encounter in the real case scenarios. By the definition of softmax score, the sum of all scores across all bending angle classes is equal to 1. We observed from Table 1 that, for each individual test set, the CNN model has assigned most of the score to the adjacent bending angle classes to the test bending angle (over 90 %). In addition, the closer the test bending angle is to the training bending angle classes the higher the scores. During the actual surgical operation, when the test bending angle is actually unknown, this prediction would provide us with a reasonable estimation of the bending angle. More importantly, the prediction results allow us to select two winning models, namely $LSTM_{k_1}$ and $LSTM_{k_2}$, and the softmax scores are then used in stage two to compute the weighted average for force prediction.

4.5 STAGE TWO RESULTS

Figure.49 shows the stage two distal force prediction results for cumulative bending angles 170° , 225° , 315° , and 400° , respectively. As we can observe from plots (a)-(d), by using an LSTM model trained with a smaller bending angle than the testing bending angle would result in over-predictions as compared to ground-truth FBG readings, whereas by using an LSTM model trained with larger bending angle produces under-predicted forces. This tendency accords with the TSM characteristics as described in Figure.39 , i.e., with smaller bending angles there is smaller system friction; thus, the distal-end force is expected to be larger given the same proximal-end force, and vice versa. Therefore, the actual distal-end force falls in between the two selected LSTM models' predictions. Plots (e)-(h) demonstrate that the algorithm can track the distal force in different hysteresis phases and the error is relatively higher in the transition phase. A potential solution is discussed in future work.

Table 3 LSTM prediction results

	k_1 bending angle	k_2 bending angle	Weighted average	Mean RMSE
	RMSE	RMSE	RMSE	
φ : 170°	0.2872 N	0.1864 N	0.0918 N	0.1197 N
φ : 225°	0.3077 N	0.3528 N	0.1095 N	
φ : 315°	0.3149 N	0.5098 N	0.1008 N	
φ : 400°	0.2061 N	0.2920 N	0.1767 N	

In this approach, we use the models' softmax scores to compute the final distal-end force prediction, which is plotted in red in Figure.49. From Table 2, we can see that the weighted average prediction demonstrates a better estimation than by using merely one adjacent bending angle LSTM model, namely k_1 and k_2 bending angles. The mean RMSE for the

proposed approach is 0.1197 N. Moreover, we have observed that the algorithm makes more accurate predictions in the ① pulling and ② releasing phases than in the ③ transition phase. This observation also conformed with the learned force hysteresis profiles of different testing bending angles, as shown in Figure.49 (e)-(f).

Figure 49 Stage two prediction result

In order to demonstrate the performance of this approach, the prediction results are plotted together with the actual distal force measured by the FBG force sensor. (a) Force prediction 170°. (b) Force prediction 225°. (c) Force prediction 315°. (d) Force prediction 400°. In addition, corresponding force hysteresis profiles are plotted. (e) Hysteresis profile 170°. (f) Hysteresis profile 225°. (g) Hysteresis profile 315°. (h) Hysteresis profile 400°.

The X-axis and Y-axis interval are maintained at a 2:1 ratio to better visualize the shape of different hysteresis profiles. The algorithm can robustly identify the three hysteresis phases, more importantly, it adapts to the changing slope in phase ① and ② across different cumulative bending angles, both of which are valuable traits that conventional mathematical modelling methods do not bear. However, the distal-end force prediction in phase ③ demonstrates more errors such as under-prediction, over-prediction, and fluctuation. The maximum error occurred in these predictions ranges from 0.3 N to 0.5 N. There are two main reasons for this phenomenon. Firstly, the distal-end force in phase ③ is affected greatly when considering different cumulative bending angles. Secondly, when the FBG-based force sensor is used to measure the distal-end force for the training data labelling, the sensor is essentially measuring the compression force on the associated sheath. As a result, when the system friction changes direction in transition phase ③, there is a micro-movement observed in the sheath and sometimes unexpected contact with its neighbouring sheaths. Therefore, the distal-end force measured in this particular phase is more susceptible to the system disturbance as compared to other approaches that feature a load cell fixed on a stand, which is more prevalent in the literatures [24, 26, 84]. This is also one of the key challenges of applying FBG-based force sensor directly on the NOTES robot end-effector as it may pick up unforeseen wavelength shift during complicated surgical procedures which does not reflect the actual tension change in the tendon itself.

The time taken to collect all the training data for this approach is around 26 hours. The total training time for CNN and LSTM models is 11.4 hours. Our PC configuration is as follows: Intel® Xeon® CPU E5-1620 v2 @ 3.70GHz, RAM-16.0 GB, and NVIDIA GeForce GTX 1080 Ti. In stage one, the probing process itself lasts for 10 s after initializing the system and the times took to process an RP and make a prediction with the CNN model are 75.7 ms and

4.54 ms, respectively. In stage two, the average time needed for force prediction for one time step is 0.311 ms, which is sufficient for the 1000 Hz sampling-rate use case.

4.6 CLASSIFICATION VS REGRESSION

Table 4 Vanilla OHE CNN results

	k_1 bending angle: score	k_2 bending angle: score	RMSE	Mean RMSE
φ : 170°	150°: 0.0003	180°: 0.9988	0.0863 N	0.1788 N
φ : 225°	210°: 0.2521	240°: 0.7384	0.1993 N	
φ : 315°	300°: 0.7652	330°: 0.2335	0.1400 N	
φ : 400°	390°: 0.0243	420°: 0.9616	0.2854 N	

Table 5 Regression CNN results

	Model prediction	k_1 : weightage	k_2 : weightage	RMSE	Mean RMSE
φ : 170°	151.16°	150°: 0.9613	180°: 0.0387	0.0786 N	0.2039 N
φ : 225°	230.50°	210°: 0.3167	240°: 0.6833	0.1269 N	
φ : 315°	306.42°	300°: 0.7860	330°: 0.2140	0.3399 N	
φ : 400°	392.46°	390°: 0.9180	420°: 0.0820	0.2704 N

Figure 35 Accuracy comparison between diffused OHE, vanilla OHE, and regression.

As discussed in Section 4.3.1, besides using diffused OHE technique, we have also considered applying vanilla OHE labelling and building the CNN as a regression model. For the CNN regression model, the training data are directly labelled by their corresponding cumulative bending angles: $\{90^\circ, 120^\circ, \dots, 420^\circ, 450^\circ\}$. Consequently, when given a testing RP, a prediction is given in the form of an estimated bending angle. Then two models are selected from the LSTM pool which are adjacent to the predicted bending angle. E.g. the CNN model outputs 100° , then $LSTM_{90^\circ}$ and $LSTM_{120^\circ}$ will be selected. The force prediction is computed by using linear interpolation.

Table 3-4 show the experimental results by using vanilla OHE and regression technique. The same testing dataset was used in this case, namely, $\{170^\circ, 225^\circ, 315^\circ, 400^\circ\}$. The goal of stage one bending angle estimation is to select the best performing LSTM models

and compute weighting for the second stage. As compared to diffused OHE model, although the vanilla OHE model selects the same LSTM force prediction models, the algorithm showed a tendency to be overly dependent on one of the training bending angle classes which is commonly referred to as to produce ‘harder’ predictions. As a result, the mean RMSE goes up to 0.1788 N for the vanilla OHE CNN model. The regression approach suffers from the similar problem and has a mean RMSE of 0.2039 N. Therefore, the CNN classification model with diffused OHE is adopted for this approach as it produces a ‘softer’ score when the testing bending angle falls in between two training bending angles.

4.7 ROBUSTNESS AGAINST BENDING ANGLE DISTRIBUTION

Robot-assisted NOTES are mostly used to perform Endoscopic Submucosal Dissection (ESD) which is an advanced surgical procedure used to remove early-stage gastrointestinal tumours in the stomach or colon.[149] When the endoscope delivers the robotic arms to the patient's stomach, through the oesophagus, the path configuration is relatively predictable, as shown in Figure.51 , path 1. On the other hand, when ESD is conducted in the patient's colon, the endoscope enters via the rectum and reaches the surgical site through the intestinal tract. The configuration of the large intestine doesn't vary drastically from patients to patients, however, the bending angle distribution could be slightly different depending on patients' size, bodily position and individual difference.

Table 6 Configuration with different bending angle distribution

	k_1 : score	k_2 : score	k_3 : score	RMSE	Mean RMSE
360° config_1	330°: 0.1146	360°: 0.7386	390°: 0.1362	0.1448 N	0.1711 N
360° config_2	330°: 0.1422	360°: 0.6922	390°: 0.1515	0.1487 N	
280° config_1	270°: 0.5934	300°: 0.3741	n.a	0.1982 N	
280° config_2	270°: 0.7201	300°: 0.2297	n.a	0.1846 N	
410° config_1	390°: 0.2071	420°: 0.7543	n.a	0.1797 N	
410° config_2	390°: 0.1805	420°: 0.7775	n.a	0.1708 N

Figure 36 There are two common paths taken endoscopically during surgical operations, through the oesophagus and the large intestine.

Figure 52 Three different distributions with the same cumulative bending angle are demonstrated.

According to Equation (1-3), the force hysteresis profile is essentially determined by the cumulative bending angle φ in the TSM. In addition, it was proven by a series of experiments [26] that when given the same cumulative bending angle but different bending angle distribution, the TSM demonstrates identical friction force profiles. Moreover, to

further validate the algorithm's robustness in this regard, we tested the TSM configurations of a fixed cumulative bending angle with three different bending angle distributions. Figure.52 depicts a cumulative bending angle of 360° with three different bending angle distributions, where (a) simulates patients with a bigger size, (b) simulates patients with a smaller size, and (c) simulates the cases where there are sharper angles in between the transverse colon and the descending colon. Configuration (a) is used when collecting training data for $LSTM_{360^\circ}$, (b) and (c) are referred to as test_config_1 and test_config_2, respectively. Note that for this case we take 3 LSTM models for force prediction because that the summed softmax score of k_1 and k_2 is lower than 0.9 which only happens when the testing cumulative bending angle is very close to one of the training bending angle. The result RMSEs are 0.1448 N and 0.1487 N, respectively. We found that the RMSE is slightly higher when considering various bending angle distributions. This is verified with another two cases when the cumulative bending angles are 280° and 410° where we set-up the testing angle distributions to be dissimilar to the training angle distributions. As shown in Table 5, the mean RMSE is 0.1711 N which is sufficient for the NOTES surgical use, and this is a more practical error estimation.

Chapter 5: Conclusion and Future Works

This final chapter concludes the results of the current research progress and plans for the next stage of study. The chapter consists of three main sections. The first section summarizes the major contributions of the PhD work. The second section shows novelties of the proposed approaches. The last section include recommendations for future work.

5.1 SUMMARY OF CONTRIBUTIONS

Tendon-sheath mechanism (TSM) is widely adopted in the development of NOTES robotic systems. TSM enjoys benefits such as small size, high manoeuvrability, light weight, good payload delivery and low cost, making it the ideal choice for force/movement transmission of flexible multi-degrees of freedom surgical robots. However, the intrinsic non-linearity associated with TSM makes the application much more challenging than rigid body transmission in aspects such as control and acquiring distal haptic information. The nonlinear friction between the tendon and the sheath results in phase-dependent tension loss during the transmission. In the meantime, the friction creates dead-zone in the force hysteresis profile and backlash in the tendon movement.

We have developed a novel TSM-driven robotic suturing system to endoscopically suture defects resulted from complex flexible endoscopic procedures with stitches and knots which are not possible with existing endoscopic closure devices. There are two arms used in a suturing procedure: a needle driver for stitching and a grasper for manoeuvring objects. The needle driver ensures efficient and reliable needle manipulation, and the grasper assists by

handling tissue and suture threads. Both articulated arms have five DOFs and are intuitively controlled by the surgeon at the master console for dual-arm suturing. This TSM-driven system is leveraged to collect training and testing data to validate and compare the effectiveness of different methods.

Traditional force sensors are not adopted in TSM design due to several drawbacks such as size constraints, wiring issue, harsh working environment, and sterilization issues. As a result, mathematical modelling approaches were considered as potential substitutes. Various models were established for this purpose including a number of static friction models as well as dynamic friction models. However, these approaches were not implemented in real-life robot-assisted NOTES systems mainly due to prediction discontinuities when system operates in the vicinity of zero velocity, complications of hysteresis phase identification, and complex ad-hoc system parameter derivation process.

Therefore, to overcome the aforementioned difficulties, the author presents a data-driven approach. In the known sheath configuration scenario, the study investigated the performance of deep ANNs on predicting the distal-end force of TSMs based on only proximal-end sensory data from surgical robotics system. When sufficient data was provided for the training, the proposed RNN-LSTM approach produced good force prediction results with RMSE of 0.0219 N and 0.0975 N on system with a constant operation velocity and varying operation velocity, respectively. LSTM demonstrated superior prediction accuracy during the system transition phases and better capability in identifying the actual force hysteresis profile of TSM compared with the performance of the mathematical modelling approach and MLP. In addition, applying deep learning to force prediction enjoys the benefit of avoiding complicated parameter identification process and manually specifying the transition phases. It was also perceived that training LSTM with deficient or improper data would distinctively degrade its performance. By incorporating non-periodic motion trajectory

with varying velocity in training data collection, the accuracy of the prediction for more realistic manipulations was significantly improved. Moreover, to reduce the training effort, it was possible to train an LSTM model with force response of a spring and make a satisfactory prediction for manipulations on biological tissues. The development of deep ANN approach reinforces the surgeons' surgical capabilities and shortens the intraoperative time by adding force feedback to haptic devices while avoiding integrating additional sensors at the distal ends of surgical robots.

In addition, further research was conducted to approach unknown sheath configuration force prediction by taking a two-step approach. The author proposed an approach that firstly estimate the current system bending angle by processing an RP constructed from the sensory feedbacks during a probing process. Then, two pre-trained LSTM models are selected to make dynamic distal-end force prediction during system operation. Instead of validating this algorithm on a simulated platform set-up, we adopted the state-of-the-art FBG-based force sensor so that tendon tension could be directly measured on the actual surgical robot in order to ensure the practicality of the proposed approach. The algorithm can robustly adapt to different force hysteresis profiles, accurately identify hysteresis phases, and has a RMSE of 0.1711 N. In addition, the cumulative bending angle estimation obtained from this approach could also facilitate the conventional modelling methods that require known bending angle information to be incorporated in practice.

5.2 NOVELTIES

Modelling the non-linearity of the TSM and estimating the distal-end force is a widely studied research area because of its usefulness in enhancing control precision and establishing haptic feedback for surgeons. This Ph.D. work's novelties in tackling this problem could be summarized as the following:

1. Attacking the problem from a different angle. Instead of exhaustively exploring every factor that might affect the distal-proximal force non-linear relationship and identifying the optimal mathematical parameters, the author took a data-driven approach and customized suitable deep learning architectures to learn this relationship. The benchmark result proves this approach to be more accurate and robust to the change of unknown parameters.
2. Handling unknown TSM configuration information. The main challenge of applying conventional mathematical modelling approaches in the real-life applications lies in their assumptions of fixed TSM configuration and known cumulative bending angle. The author proposed a novel deep learning approach that predicts TSM configuration through recurrence plots. This capability not only is the foundation of ensuring the accuracy of deep learning based approach but also has the potential of improving mathematical modelling based approaches.
3. Endoscopic surgical system real-time information utilization. The accuracy of any prediction method relies heavily on the variety of available data input as well as the quality of the data. There are many sources of data in endoscopic TSM surgical robot, however, mathematical modelling approaches only utilizes load cell and encoder reading which implies some potential is left on the table.

The deep learning approach provides us the platform to incorporate all possible data measured from the endoscopic system, even at difference sampling rate, which includes force, displacement, surgeon's input gesture, endoscopic video. This novelty improves possibility of higher accuracy of estimations and also open up opportunities of building a more comprehensive architecture which the author will further discuss in Section 5.3 future work.

5.3 FUTURE WORK

The ultimate goal of force prediction is to realize haptic feedback on flexible tendon-driven NOTES robots without additional sensors at the distal-end. However, there is room to improve the accuracy & robustness of the algorithms, and also taking next steps to actually incorporate this technique with the surgical robot. Therefore, I have summarized the following future work that would strive meaningful improvements:

- Algorithm adaptation from experimental setup towards in-vivo life surgical setup:
Our methods are proven effective and accurate in our ex-vivo experimental setup which is designed to the best of our abilities to mimic the actual surgical scenario. However, there might still be discrepancies in the friction conditions and other disturbances once the robot is deployed into the intestines. Further efforts are to be made to estimate the impact of these factors and work out an adaptation strategy to ensure the robustness of the algorithm in the surgical application.
- Improve the robustness of the algorithm by incorporating additional real time information. The development of algorithm at the current stage focuses on fully utilizing sensory data from the proximal-end to make accurate predictions of the distal-end force. Other format of information could possibly enhance the

performance of the algorithm such as making use of the real-time visual video data. One promising research direction would be to customize a hybrid architecture that takes high-frequency sensory data from the proximal-end as well as low-frequency image data from the endoscope frontal camera as inputs to make a more robust prediction of the distal-end force. The main challenge facing this approach would be how to synchronize two time-series data without largely compromising the information it carries. In addition, finding the correlation between two sequential images and extracting meaningful end-effector movement information would be a critical component of such an architecture.

- Better architectures to be designed to further improve the prediction accuracy of this data-driven approach especially in the transition phase when the system operates with changing velocity as well as when the system experiences unforeseen disturbance. There are three drivers of this issue we could look into improving: 1. Design a better data collection process so that the training data includes samples of disturbance scenarios for the ML models to learn to counteract. 2. Design more sophisticated model structures such as incorporating dropout, batchnorm, skip connections, and potentially attention mechanisms in order to develop better resistance to disturbance and outliers data points. 3. Improve signal processing techniques. The current models incorporated relatively naive methods such as low-pass filters. More customized signal processing techniques could further drive down the prediction error.
- Moreover, collecting training data for LSTM is evidently tedious and toilsome work. The possibility of improving transfer learning techniques by enabling the LSTM to learn the low-level features from spring payload training data and then learn the high-level features from a smaller amount of tissue payload training data

is a good plus to the overall strategy. Transfer learning would also open up new options for us when deploying in the algorithm in real world applications where we could build a pre-trained model trained with large amount of tissue data; end-users will only need to fine-tune the model with relatively short training time to tailor the algorithm to their particular application, similar to how we use BERT.

- A critical part of the future work is to practically implement haptic feedback to real-time surgery applications. To achieve this, 2 main challenges need to be tackled: 1. Display with predicted force information onto the surgeon's hand in a way that it does not introduce vibration. Simply feedback the force will result in unstable hand movement due to the effort of the surgeon trying to balance the haptic feedback. 2. Integration of the force prediction ecosystem and surgical robot control ecosystem. Right now the robot runs on MATLAB SIMULINK and Deep Learning algorithms are primarily running on Python. Communication between the two ecosystems need to be established with the consideration of incorporating GPU as video process might enter into play in the future.
- Finally, data-driven method is an emerging field of study in the modern society where we have an explosion of available data in various systems that was previously difficult to analyse and control [150]. Many data-driven methods are being developed for the purpose of nonlinear dynamical system identification [151], robust optimal control [152] and system performance evaluation [153]. As the accumulating system data of surgical systems grows, it would be possible in the future to explore more robust methods of improving tendon-sheath control, extracting surgical surges from surgeon's input and partially automate the surgical system.

In a nutshell, the future work should focus on further enhancing the accuracy and efficiency of the data-driven models used for learning haptic information and TSM hysteresis profiles by improving algorithm architecture and data collection process. Secondly, implement this haptic feedback algorithm and overcome practical challenges. Improvements on the control accuracy of the tendon-driven robot is necessary as the naïve control scheme introduces a considerable degree of nonlinear backlash hysteresis that affects the instruments' movement precision. In addition, it creates a steep learning curve for the master-slave device for novices. Furthermore, the exploration should also include incorporating novel sensor approaches to facilitate the process of collecting system data. Improvements in this front will help to expand the possibilities of applying data-driven methods to more aspects of studying surgical robotic systems as well as to enhance the accuracy of previous methods. Finally, a comprehensive subject study will be conducted to find out the effectiveness of the haptic feedback by assessing how much this technique improves endoscopic surgical accuracy and reduces surgery time.

Conference and Journal Publications

- **Li, Xiaoguo** & Tiong, Anthony & Cao, Lin & Lai, Wenjie & Phan, Phuoc Thien & Phee, Soo. (2019). Deep Learning for Haptic Feedback of Flexible Endoscopic Robot without Prior Knowledge on Sheath Configuration. International Journal of Mechanical Sciences. 105129. 10.1016/2019.105129. *Impact Factor: 4.61*
- **Li, Xiaoguo** & Cao, Lin & Tiong, AnthonyMengHuat & Phan, Phuoc Thien & Phee, Soo. (2019). Distal-End Force Prediction of Tendon-Sheath Mechanisms for Flexible Endoscopic Surgical Robots using Deep Learning. Mechanism and Machine Theory. 134. 323-337. 10.1016/j.mechmachtheory.2018.12.035. *Impact Factor: 3.31*
- Cao, Lin & **Li, Xiaoguo** & Phan, Phuoc Thien & Kaan, Hung Leng & Liu, Jiajun & Lai, Wenjie & Huang, Yanpei & Huu Minh, Le & Miyasaka, Muneaki & Ho, Khek & Chiu, Philip & Phee, Soo. (2019). Sewing up the Wound: A Robotic Suturing System for Flexible Endoscopy. IEEE Robotics & Automation Magazine. PP. 10.1109/MRA.2019.2963161. *Impact Factor: 4.25*
- Cao, Lin & **Li, Xiaoguo** & Phan, Phuoc Thien & Tiong, Anthony & Liu, Jiajun & Phee, Soo. (2019). A Novel Robotic Suturing System for Flexible Endoscopic Surgery. 10.1109/ICRA.2019.8794247. *Conference paper*
- Cao, Lin & **Li, Xiaoguo** & Phan, Phuoc Thien & Tiong, A & Kaan, Hung Leng & Ho, Kwan Yi & Chiu, Philip & Phee, S. (2019). A Flexible Endoscopic Robotic Suturing System for Gastrointestinal Perforations: Animal Study. 97-98. 10.31256/HSMR2019.49. *Conference paper*

- Lai, Wenjie & Cao, Lin & Tan, Rex Xiao & Tan, Yung & **Li, Xiaoguo** & Phan, Phuoc Thien & Tiong, Anthony & Tjin, Swee & Phee, Soo. (2019). An Integrated Sensor-Model Approach for Haptic Feedback of Flexible Endoscopic Robots. *Annals of Biomedical Engineering*. 10.1007/s10439-019-02352-8. *Impact Factor: 3.32*

References

- [1] G. G. Hamad and M. Curet, "Minimally invasive surgery," *The American Journal of Surgery*, vol. 199, no. 2, pp. 263-265, 2010.
- [2] S. J. Phee, S. C. Low, V. A. Huynh, A. P. Kencana, Z. L. Sun, and K. Yang, "Master and slave transluminal endoscopic robot (MASTER) for natural Orifice Transluminal Endoscopic Surgery (NOTES)," in *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2009, pp. 1192-1195.
- [3] Konstantinova J, Jiang A, Althoefer K, Dasgupta P and Nanayakkara T (2014) Implementation of tactile sensing for palpation in robot-assisted minimally invasive surgery: A review. *IEEE Sensors Journal* 14(8): 2490-2501.
- [4] Khoshnam M, Skanes AC and Patel RV (2015) Modeling and estimation of tip contact force for steerable ablation catheters. *IEEE Transactions on Biomedical Engineering* 62(5): 1404-1415.
- [5] B. K. Dinh, M. Xiloyannis, L. Cappello, C. W. Antuvan, S.-C. Yen, and L. Masia, "Adaptive backlash compensation in upper limb soft wearable exoskeletons," *Robotics and Autonomous Systems*, vol. 92, pp. 173-186, 2017/06/01/ 2017.
- [6] H. Dong, E. Asadi, C. Qiu, J. Dai, and I. M. Chen, "Geometric design optimization of an under-actuated tendon-driven robotic gripper," *Robotics and Computer-Integrated Manufacturing*, vol. 50, pp. 80-89, 2018/04/01/ 2018.
- [7] B. P. M. Yeung and T. Gourlay, "A technical review of flexible endoscopic multitasking platforms," *International Journal of Surgery*, vol. 10, no. 7, pp. 345-354, 2012/01/01/ 2012.
- [8] Roy R, Wang L and Simaan N (2017) Modeling and estimation of friction, extension, and coupling effects in multisegment continuum robots. *IEEE/ASME Transactions on Mechatronics* 22(2): DOI: 10.1109/TMECH.2016.2643640.
- [9] Hasanzadeh S and Janabi-Shari F (2016) Model-based Force estimation for intracardiac catheters. *IEEE/ASME Transactions on Mechatronics* 21(1): 154-162

- [10] Trejos A, Patel R and Naish M (2010) Forcesensing and its application in minimally invasive surgery and therapy: a survey. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science* 224(7): 1435-1454
- [11] Xu K and Simaan N (2008) An investigation of the intrinsic force sensing capabilities of continuum robots. *IEEE Transactions on Robotics* 24(3): 555-561.
- [12] Xu K and Simaan N (2006) Actuation compensation for flexible surgical snake-like robots with redundant remote actuation. In: *Proceedings 2006 IEEE International Conference on Robotics and Automation, 2006. ICRA2006. IEEE*, pp. 4148-4154.
- [13] Xu K and Simaan N (2010) Intrinsic wrench estimation and its performance index for multisegment continuum robots. *IEEE Transactions on Robotics* 26(3): 555-561.
- [14] Z. Wang, Z. Sun, and S. J. Phee, "Haptic feedback and control of a flexible surgical endoscopic robot," *Computer Methods and Programs in Biomedicine*, vol. 112, no. 2, pp. 260-271, 2013/11/01/ 2013.
- [15] S. Ehrampoosh, M. Dave, M. A. Kia, C. Rablau, and M. H. Zadeh, "Providing haptic feedback in robot-assisted minimally invasive surgery: A direct optical force-sensing solution for haptic rendering of deformable bodies," *Computer Aided Surgery*, vol. 18, no. 5-6, pp. 129-141, 2013/09/01 2013.
- [16] A. M. Okamura, "Haptic Feedback in Robot-Assisted Minimally Invasive Surgery," *Current opinion in urology*, vol. 19, no. 1, pp. 102-107, 2009.
- [17] T. Akinbiyi *et al.*, "Dynamic Augmented Reality for Sensory Substitution in Robot-Assisted Surgical Systems," in *2006 International Conference of the IEEE Engineering in Medicine and Biology Society*, 2006, pp. 567-570.
- [18] M. Tavakoli, A. Aziminejad, R. V. Patel, and M. Moallem, "Methods and mechanisms for contact feedback in a robot-assisted minimally invasive environment," *Surgical Endoscopy And Other Interventional Techniques*, vol. 20, no. 10, pp. 1570-1579, 2006/10/01 2006.
- [19] D. Grant, O. R. Astley, V. Hayward, M. Cruz - Hernandez, and G. Robles - De - La - Torre, "Haptic interfaces and devices," *Sensor Review*, vol. 24, no. 1, pp. 16-29, 2004/03/01 2004.
- [20] W. Lai, L. Cao, Z. Xu, P. T. Phan, P. Shum, and S. J. L. Phee, "Distal End Force Sensing with Optical Fiber Bragg Gratings for Tendon-Sheath Mechanisms in Flexible Endoscopic Robots," in *IEEE International Conference on Robotics and Automation (ICRA)*, Brisbane, Australia, 2018.

- [21] M. Kaneko, M. Wada, H. Maekawa, and K. Tanie, "A new consideration on tendon-tension control system of robot hands," in *Proceedings. 1991 IEEE International Conference on Robotics and Automation*, 1991, pp. 1028-1033 vol.2.
- [22] T. N. Do, T. Tjahjowidodo, M. W. S. Lau, and S. J. Phee, "Nonlinear friction modelling and compensation control of hysteresis phenomena for a pair of tendon-sheath actuated surgical robots," *Mechanical Systems and Signal Processing*, vol. 60, pp. 770-784, 2015/08/01/ 2015.
- [23] B. K. Dinh, L. Cappello, M. Xiloyannis, and L. Masia, "Position control using adaptive backlash compensation for bowden cable transmission in soft wearable exoskeleton," in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2016, pp. 5670-5676.
- [24] T. N. Do, T. Tjahjowidodo, M. W. S. Lau, and S. J. Phee, "An investigation of friction-based tendon sheath model appropriate for control purposes," *Mechanical Systems and Signal Processing*, vol. 42, no. 1, pp. 97-114, 2014/01/01/ 2014.
- [25] T. N. Do, T. Tjahjowidodo, M. W. S. Lau, T. Yamamoto, and S. J. Phee, "Hysteresis modeling and position control of tendon-sheath mechanism in flexible endoscopic systems," *Mechatronics*, vol. 24, no. 1, pp. 12-22, 2014/02/01/ 2014.
- [26] T. N. Do, T. Tjahjowidodo, M. W. S. Lau, and S. J. Phee, "A new approach of friction model for tendon-sheath actuated surgical systems: Nonlinear modelling and parameter identification," *Mechanism and Machine Theory*, vol. 85, pp. 14-24, 2015/03/01/ 2015.
- [27] Z. Wang, Z. L. Sun, and S. J. Phee, "Haptic feedback and control of a flexible surgical endoscopic robot," (in English), *Computer Methods and Programs in Biomedicine*, vol. 112, no. 2, pp. 260-271, Nov 2013.
- [28] V. Vitiello, S. Lee, T. P. Cundy, and G. Yang, "Emerging Robotic Platforms for Minimally Invasive Surgery," *IEEE Reviews in Biomedical Engineering*, vol. 6, pp. 111-126, 2013.
- [29] J. H. Palep, "Robotic assisted minimally invasive surgery," *Journal of Minimal Access Surgery*, vol. 5, no. 1, pp. 1-7, Jan-Mar
- [30] Y. M. Dion and F. Gaillard, "Visual integration of data and basic motor skills under laparoscopy," *Surgical Endoscopy*, vol. 11, no. 10, pp. 995-1000, 1997/10/01 1997.
- [31] G. T. Sung and I. S. Gill, "Robotic laparoscopic surgery: a comparison of the da Vinci and Zeus systems," *Urology*, vol. 58, no. 6, pp. 893-898, 2001/12/01/ 2001.

- [32] C. M. Hollands, L. N. Dixey, and M. J. Torma, "Technical assessment of porcine enteroenterostomy performed with ZEUS™ robotic technology," *Journal of Pediatric Surgery*, vol. 36, no. 8, pp. 1231-1233, 2001/08/01/ 2001.
- [33] D. H. Boehm, C. Detter, M. B. Arnold, T. Deuse, and H. Reichenspurner, "Robotically assisted coronary artery bypass surgery with the ZEUS telemanipulator system," *Seminars in Thoracic and Cardiovascular Surgery*, vol. 15, no. 2, pp. 112-120, 2003/04/01/ 2003.
- [34] F. Pugin, P. Bucher, and P. Morel, "History of robotic surgery : From AESOP® and ZEUS® to da Vinci®," *Journal of Visceral Surgery*, vol. 148, no. 5, Supplement, pp. e3-e8, 2011/10/01/ 2011.
- [35] A. Shafer and J. F. Boggess, "Robotic-assisted endometrial cancer staging and radical hysterectomy with the da Vinci® surgical system," *Gynecologic Oncology*, vol. 111, no. 2, Supplement, pp. S18-S23, 2008/11/01/ 2008.
- [36] M. J. H. Lum *et al.*, "The RAVEN: Design and Validation of a Telesurgery System," *The International Journal of Robotics Research*, vol. 28, no. 9, pp. 1183-1197, 2009/09/01 2009.
- [37] D. Lomanto, S. Wijerathne, L. K. Y. Ho, and L. S. J. Phee, "Flexible endoscopic robot," *Minimally Invasive Therapy & Allied Technologies*, vol. 24, no. 1, pp. 37-44, 2015/01/02 2015.
- [38] H. Ashrafian, O. Clancy, V. Grover, and A. Darzi, "The evolution of robotic surgery: surgical and anaesthetic aspects," *British Journal of Anaesthesia*, vol. 119, pp. i72-i84, 2017/12/01/ 2017.
- [39] S. N. Shaikh and C. C. Thompson, "Natural orifice transluminal surgery: Flexible platform review," *World Journal of Gastrointestinal Surgery*, vol. 2, no. 6, pp. 210-216, 06/27
- [40] G. O. Spaun, B. Zheng, and L. L. Swanström, "A multitasking platform for natural orifice transluminal endoscopic surgery (NOTES): a benchtop comparison of a new device for flexible endoscopic surgery and a standard dual-channel endoscope," *Surgical Endoscopy*, vol. 23, no. 12, p. 2720, 2009/04/10 2009.
- [41] C.-L. Lee, K.-Y. Wu, H. Su, C.-M. Han, C.-Y. Huang, and C.-F. Yen, "Robot-assisted natural orifice transluminal endoscopic surgery for hysterectomy," *Taiwanese Journal of Obstetrics and Gynecology*, vol. 54, no. 6, pp. 761-765, 2015/12/01/ 2015.

- [42] Z. Wang, S. J. Phee, J. Wong, and K.-Y. Ho, "Development of a robotic platform for natural orifice transluminal endoscopic surgery," *Gastrointestinal Intervention*, vol. 1, no. 1, pp. 40-42, 2012/12/01/ 2012.
- [43] D. J. Abbott, C. Becke, R. I. Rothstein, and W. J. Peine, "Design of an endoluminal NOTES robotic system," in *2007 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2007, pp. 410-416.
- [44] S. J. Phee, S. C. Low, V. A. Huynh, A. P. Kencana, Z. L. Sun, and K. Yang, "Master And Slave Transluminal Endoscopic Robot (MASTER) for Natural Orifice Transluminal Endoscopic Surgery (NOTES)," (in English), *2009 Annual International Conference of the Ieee Engineering in Medicine and Biology Society, Vols 1-20*, pp. 1192-1195, 2009.
- [45] S. J. Phee *et al.*, "Design of a master and slave transluminal endoscopic robot for natural orifice transluminal endoscopic surgery," (in English), *Proceedings of the Institution of Mechanical Engineers Part C-Journal of Mechanical Engineering Science*, vol. 224, no. C7, pp. 1495-1503, 2010.
- [46] A. Schmidt, B. Meier, and K. Caca, "Endoscopic full-thickness resection: Current status," (in eng), *World journal of gastroenterology*, vol. 21, no. 31, pp. 9273-9285, 2015.
- [47] N. de'Angelis *et al.*, "2017 WSES guidelines for the management of iatrogenic colonoscopy perforation," (in eng), *World journal of emergency surgery : WJES*, vol. 13, pp. 5-5, 2018.
- [48] T. H. Lüning, M. E. Keemers-Gels, W. B. Barendregt, A. C. I. T. L. Tan, and C. Rosman, "Colonoscopic perforations: a review of 30,366 patients," *Surgical Endoscopy*, journal article vol. 21, no. 6, pp. 994-997, June 01 2007.
- [49] A. Schmidt, B. Meier, and K. Caca, "Endoscopic full-thickness resection: current status," *World journal of gastroenterology: WJG*, vol. 21, no. 31, p. 9273, 2015.
- [50] A. Arezzo and M. Morino, "Endoscopic closure of gastric access in perspective NOTES: an update on techniques and technologies," *Surgical Endoscopy*, journal article vol. 24, no. 2, pp. 298-303, 2010.
- [51] G. S. Raju, I. Ahmed, G. Shibukawa, A. Poussard, and D. Brining, "Endoluminal clip closure of a circular full-thickness colon resection in a porcine model (with videos)," *Gastrointestinal Endoscopy*, vol. 65, no. 3, pp. 503-509, 3// 2007.

- [52] G. Iabichino *et al.*, "Performance of the over-the-scope clip system in the endoscopic closure of iatrogenic gastrointestinal perforations and post-surgical leaks and fistulas," *Minerva Gastroenterologica e Dietologica*, Review vol. 64, no. 1, pp. 75-83, 2018.
- [53] S. H. Chon *et al.*, "Successful closure of a gastropulmonary fistula after esophagectomy using the Apollo Overstitch and endoscopic vacuum therapy," *Endoscopy*, Note vol. 50, no. 7, pp. E149-E150, 2018.
- [54] S. V. Kantsevov and J. R. Armengol-Miro, "Endoscopic Suturing, an Essential Enabling Technology for New NOTES Interventions," (in English), *Gastrointestinal Endoscopy Clinics of North America*, Review vol. 26, no. 2, pp. 375-384, 2016.
- [55] B. P. M. Yeung and P. W. Y. Chiu, "Application of robotics in gastrointestinal endoscopy: A review," (in eng), *World journal of gastroenterology*, vol. 22, no. 5, pp. 1811-1825, 2016.
- [56] C. R. Wagner and R. D. Howe, "Force Feedback Benefit Depends on Experience in Multiple Degree of Freedom Robotic Surgery Task," *IEEE Transactions on Robotics*, vol. 23, no. 6, pp. 1235-1240, 2007.
- [57] J. Dargahi, R. Sedaghati, H. Singh, and S. Najarian, "Modeling and testing of an endoscopic piezoelectric-based tactile sensor," *Mechatronics*, vol. 17, no. 8, pp. 462-467, 2007/10/01/ 2007.
- [58] W. J. Peine and R. Howe, *Do Humans Sense Finger Deformation Or Distributed Pressure To Detect Lumps In Soft Tissue?* 1998.
- [59] M. Donati *et al.*, "A Flexible Sensor Technology for the Distributed Measurement of Interaction Pressure," *Sensors (Basel, Switzerland)*, vol. 13, no. 1, pp. 1021-1045, 01/15
- [60] S. Schostek, C. N. Ho, D. Kalanovic, and M. O. Schurr, "Artificial tactile sensing in minimally invasive surgery – a new technical approach," *Minimally Invasive Therapy & Allied Technologies*, vol. 15, no. 5, pp. 296-304, 2006/01/01 2006.
- [61] S. Schostek, C.-N. Ho, D. Kalanovic, and M. O Schurr, *Artificial tactile sensing in minimally invasive surgery - A new technical approach*. 2006, pp. 296-304.
- [62] A. E. Quaid and R. A. Abovitz, "Haptic information displays for computer-assisted surgery," in *Proceedings 2002 IEEE International Conference on Robotics and Automation (Cat. No.02CH37292)*, 2002, vol. 2, pp. 2092-2097 vol.2.

- [63] A. M. Okamura, L. N. Verner, C. E. Reiley, and M. Mahvash, "Haptics for Robot-Assisted Minimally Invasive Surgery," in *Robotics Research*, Berlin, Heidelberg, 2011, pp. 361-372: Springer Berlin Heidelberg.
- [64] L. N. Verner and A. M. Okamura, "Effects of Translational and Gripping Force Feedback are Decoupled in a 4-Degree-of-Freedom Telemanipulator," in *Second Joint EuroHaptics Conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems (WHC'07)*, 2007, pp. 286-291.
- [65] W. Semere, M. Kitagawa, and A. M. Okamura, "Teleoperation with sensor/actuator asymmetry: task performance with partial force feedback," in *12th International Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems, 2004. HAPTICS '04. Proceedings.*, 2004, pp. 121-127.
- [66] J. H. Killebrew *et al.*, "A dense array stimulator to generate arbitrary spatio-temporal tactile stimuli," *Journal of neuroscience methods*, vol. 161, no. 1, pp. 62-74, 11/28 2007.
- [67] V. Hayward, "A brief taxonomy of tactile illusions and demonstrations that can be done in a hardware store," *Brain Research Bulletin*, vol. 75, no. 6, pp. 742-752, 2008/04/15/ 2008.
- [68] A. J. Silva, O. A. D. Ramirez, V. P. Vega, and J. P. O. Oliver, "PHANToM OMNI Haptic Device: Kinematic and Manipulability," in *2009 Electronics, Robotics and Automotive Mechanics Conference (CERMA)*, 2009, pp. 193-198.
- [69] A. Tobergte *et al.*, "The sigma.7 haptic interface for MiroSurge: A new bi-manual surgical console," in *2011 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2011, pp. 3023-3030.
- [70] M. Aiple and A. Schiele, "Pushing the limits of the CyberGrasp™ for haptic rendering," in *2013 IEEE International Conference on Robotics and Automation*, 2013, pp. 3541-3546.
- [71] Subramani G and Zinn MR (2015) Tackling friction-an analytical modeling approach to understanding friction in single tendon driven continuum manipulators. In: 2015 IEEE International Conference on Robotics and Automation (ICRA). IEEE, pp. 610-617
- [72] Z. Sun, Z. Wang, and S. J. Phee, "Elongation Modeling and Compensation for the Flexible Tendon--Sheath System," *IEEE/ASME Transactions on Mechatronics*, vol. 19, no. 4, pp. 1243-1250, 2014.

- [73] F. Al-Bender, W. Symens, J. Swevers, and H. Van Brussel, "Theoretical analysis of the dynamic behavior of hysteresis elements in mechanical systems," *International Journal of Non-Linear Mechanics*, vol. 39, no. 10, pp. 1721-1735, 2004/12/01/ 2004.
- [74] B. Armstrong-Hélouvry, P. Dupont, and C. C. De Wit, "A survey of models, analysis tools and compensation methods for the control of machines with friction," *Automatica*, vol. 30, no. 7, pp. 1083-1138, 1994/07/01/ 1994.
- [75] Preisach F (1935) Über die magnetische nachwirkung. *Zeitschrift für Physik* 94(5-6): 277-302.
- [76] Zhang J, Simeonov A and Yip MC (2018) Three-dimensional hysteresis compensation enhances accuracy of robotic artificial muscles. *Smart Materials and Structures* 27(3): 035002.
- [77] Zhang J, Merced E, Sepulveda N and Tan X (2014) Modeling and inverse compensation of hysteresis in vanadium dioxide using an extended generalized prandtl-ishlinskii model. *Smart Materials and Structures* 23(12): 125017.
- [78] G. Palli and C. Melchiorri, "Model and control of tendon-sheath transmission systems," in *Proceedings 2006 IEEE International Conference on Robotics and Automation, 2006. ICRA 2006.*, 2006, pp. 988-993.
- [79] G. Palli, G. Borghesan, and C. Melchiorri, "Modeling, Identification, and Control of Tendon-Based Actuation Systems," *IEEE Transactions on Robotics*, vol. 28, no. 2, pp. 277-290, 2012.
- [80] M. Do, "Dynamic Friction Modeling and Control for Flexible Tendon-Sheath Mechanism," 2015.
- [81] T. N. Do, T. E. T. Seah, and S. J. Phee, "Design and Control of a Mechatronic Tracheostomy Tube for Automated Tracheal Suctioning," *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 6, pp. 1229-1238, 2016.
- [82] T. N. Do, T. E. T. Seah, H. K. Yu, and S. J. Phee, "Development and Testing of a Magnetically Actuated Capsule Endoscopy for Obesity Treatment," (in English), *Plos One*, vol. 11, no. 1, Jan 27 2016.
- [83] T. N. Do, T. Tjahjowidodo, M. W. S. Lau, and S. J. Phee, "Adaptive control for enhancing tracking performances of flexible tendon-sheath mechanism in natural orifice transluminal endoscopic surgery (NOTES)," (in English), *Mechatronics*, vol. 28, pp. 67-78, Jun 2015.

- [84] T. N. Do, T. Tjahjowidodo, M. W. S. Lau, and S. J. Phee, "Nonlinear friction modelling and compensation control of hysteresis phenomena for a pair of tendon-sheath actuated surgical robots," (in English), *Mechanical Systems and Signal Processing*, vol. 60-61, pp. 770-784, Aug 2015.
- [85] T. N. Do, T. Tjahjowidodo, M. W. S. Lau, and S. J. Phee, "Real-time enhancement of tracking performances for cable-conduit mechanisms-driven flexible robots," (in English), *Robotics and Computer-Integrated Manufacturing*, vol. 37, pp. 197-207, Feb 2016.
- [86] F. Al-Bender and W. Symens, "Characterization of frictional hysteresis in ball-bearing guideways," *Wear*, vol. 258, no. 11, pp. 1630-1642, 2005/06/01/ 2005.
- [87] H. Mayer, F. Gomez, D. Wierstra, I. Nagy, A. Knoll, and J. Schmidhuber, "A System for Robotic Heart Surgery that Learns to Tie Knots Using Recurrent Neural Networks," in *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2006, pp. 543-548.
- [88] C. E. Reiley, E. Plaku, and G. D. Hager, "Motion generation of robotic surgical tasks: Learning from expert demonstrations," in *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, 2010, pp. 967-970.
- [89] Y. Kassahun *et al.*, "Surgical robotics beyond enhanced dexterity instrumentation: a survey of machine learning techniques and their role in intelligent and autonomous surgical actions," *International Journal of Computer Assisted Radiology and Surgery*, vol. 11, no. 4, pp. 553-568, 2016/04/01 2016.
- [90] J. v. d. Berg *et al.*, "Superhuman performance of surgical tasks by robots using iterative learning from human-guided demonstrations," in *2010 IEEE International Conference on Robotics and Automation*, 2010, pp. 2074-2081.
- [91] R. C. Jackson and M. C. Çavuşoğlu, "Needle path planning for autonomous robotic surgical suturing," in *2013 IEEE International Conference on Robotics and Automation*, 2013, pp. 1669-1675.
- [92] 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 *2016 IEEE International Conference on Robotics and Automation (ICRA)*, 2016, pp. 4178-4185.

- [93] S. Patil and R. Alterovitz, "Toward automated tissue retraction in robot-assisted surgery," in *2010 IEEE International Conference on Robotics and Automation*, 2010, pp. 2088-2094.
- [94] S. Wang, H. Wang, and L. Yue, "A novel knot-tying approach for minimally invasive surgical robot systems," *The International Journal of Medical Robotics and Computer Assisted Surgery*, vol. 4, no. 3, pp. 268-276, 2008/09/01 2008.
- [95] W. Xu, J. Chen, and H. Lau, "Data-driven methods towards learning the highly nonlinear inverse kinematics of tendon-driven surgical manipulators: XWJ_IJMRAS_IK_KNNR_GMR_ELM," *The International Journal of Medical Robotics and Computer Assisted Surgery*, vol. 13, 01/01 2016.
- [96] W. He, T. Meng, D. Huang, and X. Li, "Adaptive Boundary Iterative Learning Control for an Euler–Bernoulli Beam System With Input Constraint," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 29, no. 5, pp. 1539-1549, 2018.
- [97] W. He, X. He, M. Zou, and H. Li, "PDE Model-Based Boundary Control Design for a Flexible Robotic Manipulator With Input Backlash," *IEEE Transactions on Control Systems Technology*, vol. 27, no. 2, pp. 790-797, 2019.
- [98] R. Zhao, R. Yan, Z. Chen, K. Mao, P. Wang, and R. X. Gao, "Deep learning and its applications to machine health monitoring," *Mechanical Systems and Signal Processing*, vol. 115, pp. 213-237, 2019/01/15/ 2019.
- [99] T. Irgolic, F. Cus, M. Paulic, and J. Balic, "Prediction of Cutting Forces with Neural Network by Milling Functionally Graded Material," *Procedia Engineering*, vol. 69, pp. 804-813, 2014/01/01/ 2014.
- [100] H. H. Savelberg and W. Herzog, "Prediction of dynamic tendon forces from electromyographic signals: an artificial neural network approach," (in eng), *Journal of neuroscience methods*, vol. 78, no. 1-2, pp. 65-74, 1997/12// 1997.
- [101] F. Bai and C.-M. Chew, "Muscle force estimation with surface EMG during dynamic muscle contractions: A wavelet and ANN based approach," *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*, vol. 2013, pp. 4589-4592, 07/01 2013.

- [102] W. He and Y. Dong, "Adaptive Fuzzy Neural Network Control for a Constrained Robot Using Impedance Learning," *IEEE Transactions on Neural Networks and Learning Systems*, vol. PP, pp. 1-13, 03/01 2017.
- [103] X. Li, L. Cao, A. Tjong, P. T. Phan, and S. Phee, "Distal-End Force Prediction of Tendon-Sheath Mechanisms for Flexible Endoscopic Surgical Robots using Deep Learning," *Mechanism and Machine Theory*, vol. 134, pp. 323-337, 01/08 2019.
- [104] H. Asada and S. Liu, "Transfer of human skills to neural net robot controllers," in *Proceedings. 1991 IEEE International Conference on Robotics and Automation*, 1991, pp. 2442-2448 vol.3.
- [105] D. R. Myers, "An approach to automated programming of industrial robots," in *Proceedings 1999 IEEE International Conference on Robotics and Automation (Cat. No.99CH36288C)*, 1999, vol. 4, pp. 3109-3114 vol.4.
- [106] B. Price and C. Boutilier, "A Bayesian approach to imitation in reinforcement learning," presented at the Proceedings of the 18th international joint conference on Artificial intelligence, Acapulco, Mexico, 2003.
- [107] P. D. van-Hove, G. J. M. Tuijthof, E. G. G. Verdaasdonk, L. P. S. Stassen, and J. Dankelman, "Objective assessment of technical surgical skills," *British Journal of Surgery*, vol. 97, no. 7, pp. 972-987, 2010.
- [108] B. Bridgewater *et al.*, "Surgeon specific mortality in adult cardiac surgery: comparison between crude and risk stratified data," *BMJ : British Medical Journal*, vol. 327, no. 7405, pp. 13-17, 06/17/accepted 2003.
- [109] C. E. Reiley, H. C. Lin, D. D. Yuh, and G. D. Hager, "Review of methods for objective surgical skill evaluation," *Surgical Endoscopy*, vol. 25, no. 2, pp. 356-366, 2011/02/01 2011.
- [110] K. Ahmed, D. Miskovic, A. Darzi, T. Athanasiou, and G. B. Hanna, "Observational tools for assessment of procedural skills: a systematic review," *The American Journal of Surgery*, vol. 202, no. 4, pp. 469-480.e6, 2011/10/01/ 2011.
- [111] S. K. Neequaye, R. Aggarwal, I. Van Herzeele, A. Darzi, and N. J. Cheshire, "Endovascular skills training and assessment," *Journal of Vascular Surgery*, vol. 46, no. 5, pp. 1055-1064, 2007/11/01/ 2007.
- [112] W. Xu, J. Chen, H. Y. K. Lau, and H. Ren, "Data-driven methods towards learning the highly nonlinear inverse kinematics of tendon-driven surgical manipulators,"

- The International Journal of Medical Robotics and Computer Assisted Surgery*, vol. 13, no. 3, p. e1774, 2017.
- [113] W. Song, Z. Weiyu, and L. Zhi-Pei, "Shape deformation: SVM regression and application to medical image segmentation," in *Proceedings Eighth IEEE International Conference on Computer Vision. ICCV 2001*, 2001, vol. 2, pp. 209-216 vol.2.
 - [114] P. Arena, A. Basile, M. Bucolo, and L. Fortuna, "Image processing for medical diagnosis using CNN," *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 497, no. 1, pp. 174-178, 2003/01/21/ 2003.
 - [115] H. Shao, K. Nonami, T. Wojtara, R. Yuasa, S. Amano, and D. Waterman, *Neuro-fuzzy position control of demining tele-operation system based on RNN modeling*. 2006, pp. 25-32.
 - [116] N. M. Nasrabadi, "Pattern Recognition and Machine Learning," 2007, vol. 16: SPIE.
 - [117] C. J. C. H. Watkins and P. Dayan, "Q-learning," *Machine Learning*, vol. 8, no. 3, pp. 279-292, 1992/05/01 1992.
 - [118] H. Ramchoun, M. A. Janati Idrissi, Y. Ghanou, and M. Ettaouil, *Multilayer Perceptron: Architecture Optimization and training with mixed activation functions*. 2017.
 - [119] F. Murtagh, "Multilayer perceptrons for classification and regression," *Neurocomputing*, vol. 2, no. 5, pp. 183-197, 1991/07/01/ 1991.
 - [120] J. T. Connor, R. D. Martin, and L. E. Atlas, "Recurrent neural networks and robust time series prediction," *IEEE Transactions on Neural Networks*, vol. 5, no. 2, pp. 240-254, 1994.
 - [121] F. K. John and C. K. Stefan, "Gradient Flow in Recurrent Nets: The Difficulty of Learning LongTerm Dependencies," in *A Field Guide to Dynamical Recurrent Networks*: IEEE, 2001, p. 1.
 - [122] P. J. Werbos, "Backpropagation through time: what it does and how to do it," *Proceedings of the IEEE*, vol. 78, no. 10, pp. 1550-1560, 1990.
 - [123] F. A. Gers, #252, r. A. Schmidhuber, and F. A. Cummins, "Learning to Forget: Continual Prediction with LSTM," *Neural Comput.*, vol. 12, no. 10, pp. 2451-2471, 2000.

- [124] H. Shin *et al.*, "Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning," *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1285-1298, 2016.
- [125] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, p. 436, 05/27/online 2015.
- [126] X. Zhai, B. Jelfs, R. H. M. Chan, and C. Tin, "Self-Recalibrating Surface EMG Pattern Recognition for Neuroprosthesis Control Based on Convolutional Neural Network," *Frontiers in neuroscience*, vol. 11, pp. 379-379, 2017.
- [127] F. Hutter, H. Hoos, and K. Leyton-Brown, "An efficient approach for assessing hyperparameter importance," presented at the Proceedings of the 31st International Conference on International Conference on Machine Learning - Volume 32, Beijing, China, 2014.
- [128] S. J. Pan and Q. Yang, "A Survey on Transfer Learning," *IEEE Transactions on Knowledge and Data Engineering*, vol. 22, no. 10, pp. 1345-1359, 2010.
- [129] S. J. Pan, J. T. Kwok, and Q. Yang, "Transfer learning via dimensionality reduction," presented at the Proceedings of the 23rd national conference on Artificial intelligence - Volume 2, Chicago, Illinois, 2008.
- [130] S. J. Phee, S. C. Low, P. Dario, and A. Menciassi, "Tendon sheath analysis for estimation of distal end force and elongation for sensorless distal end," *Robotica*, vol. 28, no. 7, pp. 1073-1082, 2010.
- [131] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning internal representations by error propagation," in *Parallel distributed processing: explorations in the microstructure of cognition*, vol. 1, E. R. David, L. M. James, and C. P. R. Group, Eds.: MIT Press, 1986, pp. 318-362.
- [132] R. Jozefowicz, W. Zaremba, and I. Sutskever, "An empirical exploration of recurrent network architectures," presented at the Proceedings of the 32nd International Conference on International Conference on Machine Learning - Volume 37, Lille, France, 2015.
- [133] J. Bergstra and Y. Bengio, "Random search for hyper-parameter optimization," *J. Mach. Learn. Res.*, vol. 13, pp. 281-305, 2012.
- [134] D. Kingma and J. Ba, *Adam: A Method for Stochastic Optimization*. 2014.
- [135] H. In, H. Lee, U. Jeong, B. Kang, and K.-J. Cho, "Feasibility study of a slack enabling actuator for actuating tendon-driven soft wearable robot without

- pretension," *Proceedings - IEEE International Conference on Robotics and Automation*, vol. 2015, pp. 1229-1234, 06/29 2015.
- [136] S. Phee, S. C. Low, P. Dario, and A. Menciassi, "Tendon sheath analysis for estimation of distal end force and elongation for sensorless distal end," *Robotica*, vol. 28, pp. 1073-1082, 12/01 2010.
- [137] Z. Wang, Z. Sun, and S. Phee, "Haptic feedback and control of a flexible surgical endoscopic robot," *Computer methods and programs in biomedicine*, vol. 112, 04/02 2013.
- [138] Z. Sun, Z. Wang, and S. Phee, "Modeling and Motion Compensation of a Bidirectional Tendon-Sheath Actuated System for Robotic Endoscopic Surgery," *Computer Methods and Programs in Biomedicine*, vol. 119, pp. 77-87, 03/18 2015.
- [139] L. Cao, X. Li, P. T. Phan, A. M. H. Tiong, J. Liu, and S. J. Phee, "A Novel Robotic Suturing System for Flexible Endoscopic Surgery," in *2019 International Conference on Robotics and Automation (ICRA)*, 2019, pp. 1514-1520.
- [140] W. Lai, L. Cao, Z. Xu, P. T. Phan, P. Shum, and S. J. Phee, "Distal End Force Sensing with Optical Fiber Bragg Gratings for Tendon-Sheath Mechanisms in Flexible Endoscopic Robots," in *2018 IEEE International Conference on Robotics and Automation (ICRA)*, 2018, pp. 1-5.
- [141] K. O. Hill, B. Malo, F. Bilodeau, D. C. Johnson, and J. Albert, "Bragg gratings fabricated in monomode photosensitive optical fiber by UV exposure through a phase mask," *Applied Physics Letters*, vol. 62, no. 10, pp. 1035-1037, 1993/03/08 1993.
- [142] F. Ren, W. Zhang, Y. Li, Y. Lan, Y. Xie, and W. Dai, "The Temperature Compensation of FBG Sensor for Monitoring the Stress on Hole-Edge," *IEEE Photonics Journal*, vol. 10, pp. 1-1, 07/25 2018.
- [143] J. P. Eckmann, S. O. Kamphorst, and D. Ruelle, "Recurrence Plots of Dynamical Systems," *Europhysics Letters (EPL)*, vol. 4, no. 9, pp. 973-977, 1987/11/01 1987.
- [144] M. Koebbe, G. Mayer-kress, and J. Zbilut, *Use of Recurrence Plots in the Analysis of Time-Series Data*. 1994.
- [145] F. A. Faria, J. Almeida, B. Alberton, L. P. C. Morellato, and R. da S. Torres, "Fusion of time series representations for plant recognition in phenology studies," *Pattern Recognition Letters*, vol. 83, pp. 205-214, 2016/11/01/ 2016.

- [146] A. Krakovská, K. Mezeiová, and H. Budáčová, *Use of False Nearest Neighbours for Selecting Variables and Embedding Parameters for State Space Reconstruction*. 2015, p. 12.
- [147] P. Rodríguez, M. A. Bautista, J. González, and S. Escalera, "Beyond one-hot encoding: Lower dimensional target embedding," *Image and Vision Computing*, vol. 75, pp. 21-31, 2018/07/01/ 2018.
- [148] A. FABRETTI and M. AUSLOOS, "RECURRENCE PLOT AND RECURRENCE QUANTIFICATION ANALYSIS TECHNIQUES FOR DETECTING A CRITICAL REGIME," *International Journal of Modern Physics C*, vol. 16, no. 05, pp. 671-706, 2005.
- [149] S. J. Phee *et al.*, "Robot-Assisted Endoscopic Submucosal Dissection Is Effective in Treating Patients With Early-Stage Gastric Neoplasia," (in English), *Clinical Gastroenterology and Hepatology*, vol. 10, no. 10, pp. 1117-1121, Oct 2012.
- [150] "Data-Driven Methods for Dynamical Systems," in *Mathematical and Computational Modeling*.
- [151] X. Kuang, X. Sui, Y. Liu, C. Liu, Q. Chen, and G. Gu, "Robust destriping method based on data-driven learning," *Infrared Physics & Technology*, vol. 94, pp. 142-150, 2018/11/01/ 2018.
- [152] W. Tang and P. Daoutidis, "Distributed adaptive dynamic programming for data-driven optimal control," *Systems & Control Letters*, vol. 120, pp. 36-43, 2018/10/01/ 2018.
- [153] Z. Hou, H. Gao, and F. L. Lewis, "Data-Driven Control and Learning Systems," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 5, pp. 4070-4075, 2017.
- [154] L. Cao, X. Li, P. T. Phan, A. M. H. Tiong, J. Liu, and S. J. Phee, "A novel robotic suturing system for flexible endoscopic surgery," in *IEEE International Conference on Robotics and Automation (ICRA)*, Montreal, Canada, 2019, pp. 1524-1520.

Appendices

Appendix A

Development of the tendon-driven endoscopic surgical robot

In this section, we introduce the endoscopic surgical robot system. The development of the tendon-driven endoscopic surgical robot serves three main purposes. First, we will ensure the practicality of the instruments through completing an actual animal study. In addition, all training data and testing data will be collected from the actual robot to make sure that it's realistic. Finally, the actual endoscopic surgical robots are usually small in size by nature. Hence, collecting ground truth data will be challenging. This forces us to come up with more practical solutions which will drive more realistic implementations.

This surgical robot development project is completed in collaboration with Dr. Cao Lin with the help of the NTU RRC surgical team including important team members: Phuoc Thien Phan, Anthony Meng Huat Tiong, Jiajun Liu, Wenjie Lai, Yanpei Huang, Huu Minh Le, and Prof. Soo Jay Phee. The project was funded by National Research Foundation Singapore. In addition, the animal study was accomplished in collaboration with Hung Leng Kaan and Prof. Khok Yu Ho from Department of Surgery, National University Hospital, Singapore.

A1. System Overview

If a perforation occurs as a result of a flexible endoscopic procedure, suturing through urgent laparoscopy or open surgery may be required to repair the perforation because suturing is normally stronger than closure using existing endoscopic devices. Suturing with stitches and knots, widely adopted in open or laparoscopic surgery, is still not possible in flexible endoscopy. This is because of the confined space of the natural orifice and target area, high levels of motion dexterity and force needed for stitching and knot-tying, and critical size and strength requirements of wound closure. We present a novel flexible endoscopic robotic suturing system that is able to suture gastrointestinal defects without opening up the patient's body like in open or laparoscopic surgery. This system features a robotic needle driver and a robotic grasper, both of which are flexible, through-the-scope (small in sizes), and dexterous with five degrees of freedom. The needle driver, facilitated by the grasper, enables the surgeon to control a needle through teleoperation to make stitches and knots in flexible endoscopy. Successful in vivo trials were conducted in the rectum of a live pig to confirm the feasibility of endoscopic suturing and knot-tying using the system in a realistic surgical scenario (not possible with existing devices which are all manually driven). This new technology will change the way how surgeons close gastrointestinal defects.

Here, we have designed and fabricated a robotic suturing system that can desirably close wounds in flexible endoscopy with stitches and knots. The system features two flexible robotic arms—a dedicated needle driver² and a grasper. The needle driver enables the surgeon to robotically manipulate a curved, double-point needle to penetrate tissue at desired locations and angles. A latching mechanism is employed to switch the needle between the

² A PCT patent on this needle driver has been filed (PCT/SG2018/050606).

two jaws of the needle driver, which is crucial to generate stitches and knots. The grasper assists the needle driver by manipulating tissues and the suture thread.

The advantageous features of the system are as follows:

- i. Flexible: the instruments are driven by flexible tendon sheath mechanisms (TSMs), suitable for the tortuous gastrointestinal (GI) tract.
- ii. Dexterous: both instruments have five degrees of freedom (DOFs), which is vital for tissue and suture manipulation in confined areas.
- iii. Through-the-Scope: the instruments are small enough to be inserted through the endoscope's tool channels, avoiding the withdrawal and re-insertion of the endoscope for tool exchanges or needle reloading.
- iv. Running stitches: stitches can be continuously created for efficient and reliable closure.
- v. Knot-tying: knots can be tied for secure closure.
- vi. Controlled/safe puncture: the surgeon can see the target tissue and needle tips, avoiding inadvertently injuries to surrounding organs [50].
- vii. Full-thickness: full-thickness closure is possible with the system, promoting strong and reliable closures of life-threatening perforations [50].
- viii. Intuitive dual-arm operation: suturing is normally done with two arms, which is now achieved by the two cooperative robotic instruments and the intuitive mapping between the master and slave manipulators.

Figure 53 The flexible endoscopic robotic suturing system

With the system, the surgeon at the master console controls two slave robotic instruments (inside the flexible endoscope) via a robotic workstation (Figure.53). Two Omega 7 interfaces (Force Dimension Inc., Switzerland) are used as the master manipulators. The workstation consists of the motor blocks, control boards, and a docking adaptor for the endoscope. The endoscope has two tool channels where the two robotic instruments—the needle driver (Ø4.4 mm) and grasper (Ø4.2 mm)—can be smoothly inserted. There is another standard channel for Ø2.5 mm manual endoscopic tools (needle injectors, Dual Knife, etc.).

A2. Needle Driver and Grasper

If a perforation occurs as a result of a flexible endoscopic procedure, suturing through The needle driver (Figure.54) has a pitch-yaw wrist and an end-effector manipulating a hollow, curved needle (gauge 21) with two lancet tips. The needle stands in-between the two

Figure 54 (a) instrument overview; (b)-(c) switching needle between two jaws; (d)-(g) stitching process.

jaws of the needle driver. A latching mechanism is employed to selectively lock the needle to one of the two jaws (Figure.54 b and c). Each jaw has a locking blade that is driven by a

TSM to lock or unlock the needle. The blades are attached to a tendon which is looped around three pulleys on the needle driver (Figure.54 c). The blades are made by securely crimping a stainless tube (Length 5.5 mm, OD/ID: 1.07mm/0.84mm) flat onto the driving tendon, avoiding the delicate and complex laser welding procedure. When the tendon is pulled at one end, the corresponding blade will be advanced to engage with the needle, and the other blade is moved back to disengage, i.e., the needle is locked to one jaw and released on the other during suturing.

The needle has a flat region on each end to constrain the needle from rotating inside the needle hole and to define the insertion depth of the needle. This ensures that the needle can always point to the needle hole on the opposite jaw and the blade can accurately slide into the corresponding slot. Note that the needle and needle holes are curved with a radius the same as that (9 mm) of the needle's motion trajectory (rotation around the gripping axis) to reduce friction and tissue trauma.

Both instruments have five DOFs (Figure.54 a): gripping, yaw, pitch, roll, and translation. Thus, they can reach target tissues with suitable orientations (without steering the endoscope) and triangulate with each other. The grasper can precisely reach the target tissue and feed it to the needle tip, preventing blind puncture to surrounding organs [54]. The roll and translation DOFs of the instruments are achieved by rolling and translating the whole bodies of the instruments using motorized linear slides and gears on the motor blocks. The main body (torque coil) of each instrument is flexible in bending but stiff in transmitting torques in the tortuous endoscope. A problem with the previous prototype is that the torque coil has large elongation which introduces motion backlash for the translation DOF. In the current prototype, this backlash issue is solved by constraining the length of the torque coil using an inner tendon which is fixed to the two ends of the torque. In addition, when the endoscope is highly tortuous and there are large external loads on the end-effector, critical

torsional backlash and un-controllable torsional snapping may still occur, which is a safety concern. Therefore, the instruments can only be rolled to adjust the orientation only when there is no external load on the end-effector.

The dimensions were selected with the following constraints: (1) the rigid sections of the instruments should be reasonable short to ensure smooth insertion of the instruments into the endoscope even when the endoscope is bend with 65 mm bending radius; (2) the instruments should at least have a cylindrical workspace of $\varnothing 25$ mm; (3) the needle driver should be able to open wide and to exert enough forces to puncture tissue that are 3 mm in thickness for full-thickness suturing; (4) the needle should be inserted into the jaws sufficiently deep to ensure stability, and the lancet tip of the needle should be sharp.

A3. Control Architecture

Each master manipulator provides a $\varnothing 160 \times 110$ mm cylindrical workspace. The translational workspace is linearly mapped to that of the end-effector. The input (with a sampling rate of 1000 Hz) from Omega.7 devices is used as the PID control reference for the two motors associated with each DOF. When one motor winds in, its counterpart unwinds. Similarly, for the gripping motion, the $[1, 28]^\circ$ master motion range is linearly mapped to the $[0, 78]^\circ$ slave motion range. Moreover, once the master graspers reach $[0, 1]^\circ$, the puncturing and grasping programs are triggered for the slave suturing device and grasper correspondingly. The needle driver will keep driving the needle through the tissue until a maximum force of 90N is reached at the proximal end; then all movement on this TSM stops. Likewise, the slave grasper also delivers 90N on the pulling tendon and will keep holding this tension until the master grasper commands to release. This ensures that even if the tissue starts to slip from the grasper, the associated tendon would timely pull more to avoid further slipping.

For the two blades that switch the needle between upper and lower jaws, the switching process is triggered using the two add-on buttons on the right-hand Omega 7 device. When the upper button is pressed, the corresponding tendon will pull the upper blade until the proximal force reaches 30 N to ensure the blade is securely in position to lock the needle onto the upper jaw. Subsequently, the pulling motor will unwind 30° to release the tension (the blade still locks the needle) which, would otherwise, inhibits the movement of other joints. The same protocol applies to the lower blade.

The load cells provide valuable information for the control architecture. During the initialization protocol, both end-effectors stay inside their channels of the endoscope, and all motors wind in until 8N is reached for the closing-jaw tendons and 4N for all other tendons. This procedure ensures the yaw and pitch joints are in the neutral position and the jaws are fully closed. When manipulating the instruments in time of surgical procedures, load cells monitor the tension in all tendons to make sure no proximal force exceeds 100N so that we do not risk severe abrasion, breaking the tendon or buckling the sheath. The proximal tension is also used as force feedback for the pitch and yaw DOFs so that the user has a sense of the forces exerted on the tendons, avoiding excessive tissue manipulation force or tendon breakage. This scheme also allows the user to feel the hands' positions in the master workspace, which improves hand-eye coordination. For the gripping motion, without a resistive force to the thumb, the user can sometimes unintentionally trigger the automated grasping or puncturing process. Thus, for each Omega 7 interface, a small resistive force is applied to the user's thumb when the master gripper is in the range of $[1, 3]^\circ$ to eliminate false maneuvers.

Figure 55 Setup for the gripping force measurement when the pitch joint is rotated

A4. In-vivo animal study

This system was tested via a pilot in vivo animal study on a live pig (about 70 kg) with approval from the Institutional Animal Care and Use Committee (NO.: INH2018/017), Singapore. The aim was to show the feasibility of using this suturing system in closing an incision endoscopically in a realistic surgical scenario. Porcine models were chosen because of the presence of similar peristalsis, intraluminal secretions, and possible complications in the human colon.

Figure.56 shows the setup. The endoscope was inserted into the pig's rectum. Following submucosal saline lift using an injection needle, a 10 mm submucosal incision was cut in the rectal mucosa using DualKnife. The needle driver and grasper were delivered to the incision site through the two channels of the endoscope. Following the deployment procedure described in [159], the needle with a 10 cm 3-0 Vicryl suture was deployed by tensioning the thin nitinol guidewire. After locking the needle to one jaw of the needle driver and removing the guidewire, four running stitches were made for the incision with the above mentioned "in-

Figure 56 In vivo animal study setup

out-out-in” pattern. The stitches were secured with a Surgeon’s Knot. A monopolar diathermy cutter ($\varnothing 2.5$ mm) was used to cut the two ends of the suture. The needle was unlocked from the suturing device and subsequently gripped and taken out by the grasper through the tool channel. After withdrawing the needle driver from the endoscope, the endoscope was removed. The animal was euthanized after the procedure.

The suturing process is shown in Figure.57. The needle driver on the right can accurately point the needle tip to the desired stitching point (Figure.57 b) and to the suture loop (Figure.57 d). Meanwhile, the grasper on the left played an important role in lifting and feeding tissue to the needle driver as well as handling the suture thread. The time for making the stitches, and creating the knot was 11 mins and 4 mins, respectively. For details, refer to the supplementary video online.

The needle locking mechanism was reliable and ensured successful needle switching during the trial. When the needle penetrated through tissue, the rotating jaw always had a snapping motion (Section V-B) and the needle tip became visible, both of which indicated that the needle was ready to be switched. Apart from the pitch and yaw DOFs, we also found

Figure 57 Suturing process. (a) robotic arms deployed at the incision site (highlighted in the blue circle); (b) driving the needle through the tissue; (c) four stitches made; (d) create surgical knot by passing the needle through suture loops; (e) securing the knot by translating the robotic arms into opposite directions; (f) cutting the suture using an electric clutch cutter; (g) withdrawing the needle using the grasper; (h) incision closed using four stitches and a Surgeon's Knot; (i) needle taken out by the grasper.

that the rolling DOF was highly important as it helps the end-effectors approach the tissue from a proper angle, which is necessary for incisions with arbitrary orientations. The through-the-scope feature is particularly useful when a new needle needs to be used for additional stitches. The feasibility of deploying the needle using a nitinol guidewire was also confirmed robust. We also confirmed that puncturing tissue with the needle on the lower jaw is much more efficient than puncturing with the needle on the upper jaw.

With the robotic suturing system, suturing is done by two cooperative robotic instruments, which naturally suits the suturing tasks. This made suturing with this system easier and more intuitive as compared with other devices. In addition, this system supports endoscopic knot-tying (not possible with other devices) and is also compatible with barbed sutures and miniaturized fasteners, giving surgeons more choices.

The current system has some limitations. Suturing in this trial took much longer time than previous ex-vivo trials because of the limitation of the system in sealing insufflation gas. The time can be significantly shortened with proper insufflation. Although the two robotic arms are dexterous in their workspaces, the movement of the endoscope manually controlled by the endoscopist does help. This can be improved via the optimal design of the instruments for larger and more dexterous workspaces. In addition, the camera's view to the needle tip and target suturing point may be blocked by the jaws of the instruments, which sometimes requires the surgeon to adjust the orientation of the instrument for a clear view. This visual occlusion may be avoided using a rotatable or steerable camera with automated algorithms. The current haptic feedback is based on proximal force sensing. Accurate distal force feedback may be enabled using force sensors or modelling to improve stitching and knot-tying. For enhanced safety and efficiency, virtual fixtures may be implemented, and they can be determined in vivo with accurate force feedback during registration. In this trial, gas insufflation was used since the colon was not fully perforated. In the case of perforations, a deployable "tent" [160] may be used to maintain the field of view. The jaws can only open 78° because of unilateral opening while bilateral opening jaws may be developed to enhance the reach of the instruments and to allow suturing for thicker tissues.

A5. Summary

Our team have developed a novel robotic suturing system to endoscopically suture defects resulted from complex flexible endoscopic procedures with stitches and knots which are not possible with existing endoscopic closure devices. The needle driver ensures efficient and reliable needle manipulation, and the grasper assists by handling tissue and suture threads. Both articulated arms have five DOFs and are intuitively controlled by the surgeon at the master console for dual-arm suturing.

Through the in vivo animal study, this suturing system, with the favorable features listed in Section I, has preliminarily demonstrated its effectiveness of closing gastrointestinal defects endoscopically in realistic surgical scenarios. Since the system enables both stitching and knot-tying, similar to laparoscopic suturing, the closure quality using our suturing method is expected to be similar to surgical closure via laparoscopy. The applications of this technology for perforations in ESD, EFTR, and NOTES are expected.

After validating the system's various capability and practicality to perform in-vivo animal trials, we will take the surgical robot to examine the performance of the force prediction approaches. The novel robotic system mainly serve the following purposes:

- Force hysteresis profile study of the actual system
- Collection of proximal-end and distal-end data used for ML algorithm training
- Validating the effectiveness of the ML algorithms during actual operating states

Appendix B

SIMULINK code for data collection