

Introduction

Surgical robots have been widely used and greatly facilitate surgical performances by bringing capability to handle versatile surgical scenes [1]. This individual research project focuses on the optimization of modeling and control of Micro-IGES surgical robot, which improves the autonomy in robotic surgery.

Micro-IGES Surgical Robots

Micro-IGES is a highly articulated surgical tool composed of a rigid shaft and flexible part, which has the features below [2].

- 6 degrees of freedom in control
- 8 degrees of freedom in modeling
- Roll, pitch and yaw motions
- Tendon-driven

Joints in each pair of elbows move for the same angle to avoid sharp bends. Joints in the articulated part are driven by pairs of tendons. Therefore, considering the complex structure of the tendon-driven configuration of Micro-IGES surgical robot, error between motion and desired path in operation is the key target which need to be optimized.

Application

Micro-IGES is the core surgical component of a single-port robotic system for transanal endoscopic surgery [3]. The system operates motions such as suturing and resection with two parallel Micro-IGES robots.

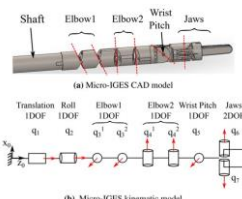


Fig.1 Model of Micro-IGES robot

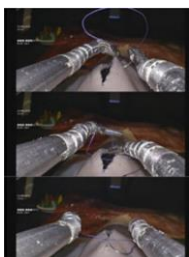


Fig.2 Test of Micro-IGES on latex model [3]

Method

Considering the complexity of tendon-driven structure and the motor-to-joint mapping, machine learning method is used in this project.

Forward Kinematics

The networks are built based on Artificial Neural Networks (ANN). The core component is a Multi-Layer Perceptron (MLP) structured by Feed-Forward Network (FFN).

- Multi-layer structure, compute derivatives efficiently
- Provide computational efficiency and potential in real-time control with smaller size
- Good for regression problems, beneficial when learning input-output mapping

Three networks are proposed to deal with different input and output,

- Feed-Forward Network (FFN) with position loss (P loss)
- AugNet with position and velocity loss (PV loss)
- AugNet_{pinv} with position, velocity and inverse loss (PVI loss)

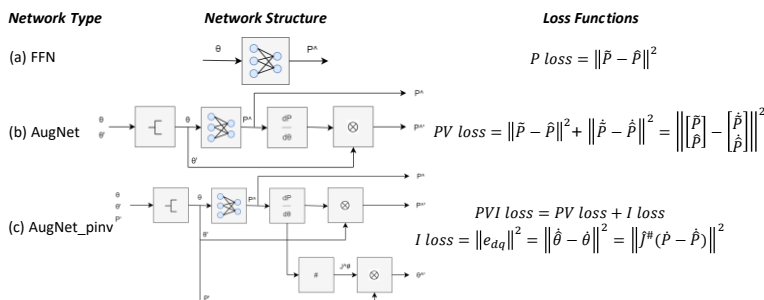


Fig.3 Network structure of (a) Feed-Forward Network, (b) AugNet and (c) AugNet_{pinv}

Inverse Kinematics

The learning of kinematics can also be achieved by inverse network. Inverse network involves the joint value and tip position in Cartesian space, so it learns the mapping from tip position P to joint value θ , it outputs θ with input P.

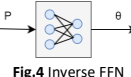


Fig.4 Inverse FFN

Results

Forward Kinematics

To analyze the modeling and control performance of network, 3 position indices are introduced.

- P_{des} : desired path
- P_{act} : motion path followed by the robot
- P_{exp} : the path which the network expects the robot is following.

The root mean square error (RMSE) represents the distance error between desired path and the path followed by the robot in the tests, which can be used to characterize the performance of network.

- RMSE: the error between P_{des} and P_{act}
- RMSE_{exp}: the error between P_{des} and P_{exp}

Model&Network

Error of P_{act} and P_{exp}

	Network	Error of P_{act} and P_{exp}	
		RMSE	RMSE _{exp}
(a) 2DoF 30_30_30	FFN	0.0281873	0.0005729
	Aug	0.0090679	5.091e-05
	AugPinv	0.0095488	3.045e-05
(b) 7DoF 60_60_60	FFN	0.082276	1.562e-07
	Aug	0.081596	1.672e-07
	AugPinv	0.106139	1.72e-07
(c) Micro-IGES 30_30_30	FFN	0.0182221	0.002679
	Aug	0.006425	2.565e-07
	AugPinv	0.002977	3.047e-07

Plot of Control and Training

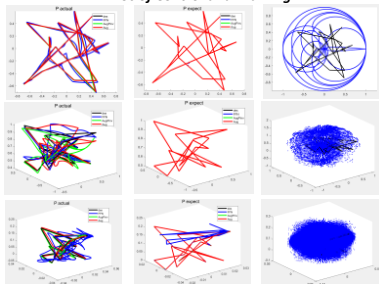


Fig.5 Result of error and path of (a) 2DoF, (b) 7DoF and (c) Micro-IGES with different network structures

Inverse Kinematics

The performance of inverse learning can be shown by the curves of expected network output and training result, as well as the mean absolute value.

	Mean Abs Value
Joint 1	0.0192
Joint 2	0.0018

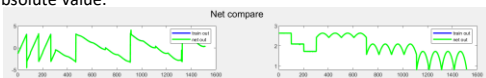


Fig.6 Result of mean absolute error and curves of 2DoF with 60_60_60 network structure

Discussion

Forward Kinematics

The RMSE_{exp} is quite small as the error between the desired path and the path expected by the network is minimized by the controller. The RMSE is larger because it is somewhat difficult for the network to learn a perfect model of robot.

Inverse Kinematics

The performance of inverse learning is not that perfect as the two curves of expected network output and the training result are not always coinciding perfectly. The inverse learning result is excellent when using dataset with less redundancy, but the performance is degraded with more general datasets.

Further Steps

Based on the progress and results so far, further steps need to be planned to optimize the modeling and control of Micro-IGES.

- Forward kinematics network needs to be improved to learn a perfect model of robot so that the RMSE may be smaller than RMSE_{exp}
- The inverse network need to be improved to have better learning result with general datasets
- Tip orientation may be added using quaternion
- Compare the performance of forward and inverse kinematics with other network structures



Fig.7 Forward learning curves of 2DoF with 30_30_30

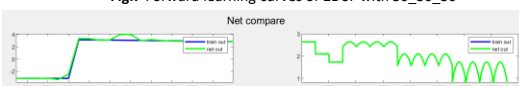


Fig.8 Errors at transition in the curves of 2DoF with 60_60_60

References

- [1] C. He, S. Wang, Y. Xing, and X. Wang, "Kinematics analysis of the coupled tendon-driven robot based on the product-of-exponentials formula," Mechanism and Machine Theory, vol. 60, pp. 90-111, 2013.
 - [2] F. Cursi, V. Modugno, and P. Korushev, "Model Predictive Control for a Tendon-Driven Surgical Robot with Safety Constraints in Kinematics and Dynamics," International Conference on Intelligent Robots and Systems (IROS 2020), Las Vegas, NV, Oct. 25-29, 2020, pp. 7653-7660.
 - [3] J. Shang, K. Leibrandt, P. Giataganas, V. Vitiello, C. A. Seneci, P. Wisanuvej, J. Liu, G. Gras, J. Clark, A. Darzi, and G. Yang, "A Single-Port Robotic System for Transanal Microsurgery—Design and Validation," IEEE Robotics and Automation Letters, vol. 2, no. 3, pp. 1510-1517, Jul. 2017.
- Ethics, grant, acknowledgement and open access information.