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Learning Based Estimation of Tool-Tissue Interaction Forces for Stationary and Moving Environments

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INTRODUCTION

Robotics-Assisted Minimally Invasive Surgery (RAMIS) has revolutionized surgical procedures by providing greater precision, flexibility, and control beyond human capabilities. However, most surgical systems in use today require surgeons to learn how to handle tissues without any haptic feedback. Recent haptic capable systems have shown reduced excessive interaction forces and the prevention of unnecessary trauma [1]. Many technical and engineering difficulties associated with sensorizing instruments exist, but neural networks have been shown to estimate these interaction forces well [2-3]. The focus of this paper is to understand the limitations of training neural networks on stationary environment ground truth data and the benefits of expanding the dataset to include moving environments.

MATERIALS AND METHODS

To collect tool-tissue interaction data where the environment is either stationary or moving, the phantom tissue is mounted on a 3 degrees-of-freedom prismatic manipulator. Trajectories are then generated with a range of parameters to mimic cardiac and respiratory motions found in surgical procedures. Mounted to the end-effector of the manipulator is a six-axes force-torque sensor which measures the ground-truth interaction forces. To estimate the interaction forces, we implemented the Feed Forward Network (FFN) approach of Chua et al. [2], the Long Short Term Memory (LSTM) network of Zhang et al. [3], and our own transformer encoder network which will be referred to as T-Enc. To evaluate each network's domain sensitivity, we train on data where the environment was stationary and then evaluate on moving environments. We then train on samples from both stationary and moving environments and test the networks sensitivity to unseen tissue location in the surgical robot's workspace.

RESULTS AND DISCUSSION

The RMSE of the force component, force magnitude, and angle are given in Table 1 for each test set split. The study reveals a clear challenge when networks trained only on stationary tissue data are tested on moving environments, showing a significant performance gap. Even in cases where the tissue's starting position matches the training data, these networks struggle to detect forces caused by motion, underscoring the limitations of stationary-only training.

Training the models with a mix of stationary and moving tissue data greatly improved their ability to predict forces in new, unseen areas. Our T-Enc model had the lowest RMSE with 0.107 N and 0.106 N for X and Y directions respectively, and 0.140 N for force magnitudes. Fig 1 shows the RMSE for binned force ranges, highlighting the significance of the range of forces present in the training set and the frequency of their occurrence.

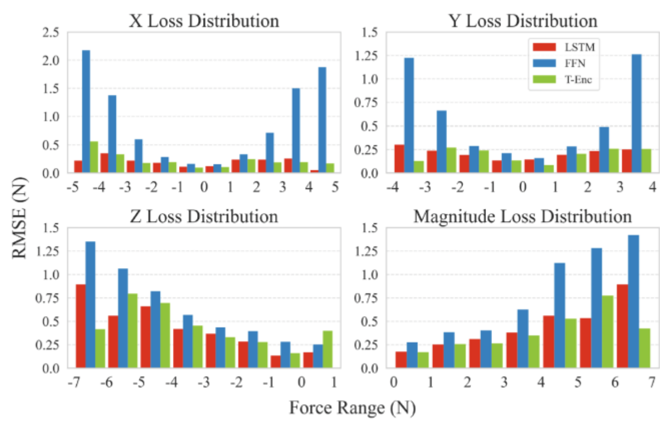

Fig 1 Binned force RMSE loss distribution for models trained on stationary and moving phantom tissue samples.

CONCLUSIONS

The study introduces a custom manipulator designed to mimic physiological motions like cardiac and respiratory movements, enhancing the realism of the testing environment. The findings emphasize the sensitivity of neural networks to the domain gap between stationary and moving tissues, underscoring the need to include both types of data in training sets for better performance.

REFERENCES

[1] Rae-Dupree, Janet. *IEEE pulse* **16.1**: 12-15, 2025.
[2] Chua, Z et al. *IEEE ICRA*: 12335-12341, 2021
[3] Zhang, J et al. *ISMR*: 1-7, 2022.

Table 1: RMSE of component force, force magnitude and force direction of S trained models on all test sets

Model	Unseen Stationary					Seen Moving					Unseen Moving				
	X	Y	Z	Mag	Angle Error	X	Y	Z	Mag	Angle Error	X	Y	Z	Mag	Angle Error
FFN	0.424	0.369	0.661	0.507	50.33	**0.476**	**0.365**	**0.872**	**0.611**	**61.79**	**0.569**	**0.488**	**1.096**	**0.766**	58.70
LSTM	**0.367**	**0.295**	**0.511**	**0.401**	**34.68**	0.556	0.443	1.108	0.760	78.71	0.712	0.533	1.108	0.820	63.38
T-Enc	0.390	0.409	0.682	0.511	36.67	3.001	4.506	4.295	3.990	61.80	4.441	4.750	4.837	4.679	**51.04**