Cycle-Consistent Neural Networks for High-Precision Force-Position Mapping in Tendon-driven Surgical Soft Robot

Yang Song[1], Bowen Su[1], Wendi Liang[1], Di Wu[2], Xin Xu[1]

***Abstract*— Accurate mapping of force and position is crucial for the management of tendon-driven surgical soft robot. We introduce a neural network framework that maintains cycle consistency, which incorporates an encoder-decoder based on convolutional neural networks (CNN) for translating force to position (measured in Newtons and meters) and a model based on Kolmogorov-Arnold networks (KAN) for the inverse kinetostatic mapping from position to force. A combined training approach, which includes distinct training phases followed by joint fine-tuning with the incorporation of cycle consistency loss, guarantees that closed-loop consistency is preserved. When tested in a tendon-driven soft robotic data set, our model demonstrates exceptional accuracy without load (forward mean square error: 0.000148 m^2; inverse mean squared error: 0.0098 N^2) and maintains strong performance under load conditions (forward mean squared error: 0.000337 m^2; inverse mean squared error: 0.0376 N^2). The cycle consistency errors are minimal (0.000217 m^2 without load, 0.000347 m^2 with load), confirming the validity of the physical consistency. With prediction durations between 0.15 and 0.25 ms per sample, this framework supports real-time control, validated through closed-loop experimental results (single-sample cycle error: 0.000217–0.000346 m^2). This method promotes enhanced precision and resilient control for tendon-driven surgical soft robot across varying load conditions.**

***Index Terms*— Cycle Consistency, Force-Position Mapping, Neural Networks, Tendon-Driven Surgical Soft Robot**

I. Introduction

Tendon-driven robots, a subset of soft robotics, offer exceptional flexibility and compliance, ideal for minimally invasive surgery and the navigation of confined spaces [1], [2]. Precise control relies on accurate force-to-position mapping, where tendon forces determine end-effector positions, and inversely, positions guide force adjustments under varying loads. In medical contexts, such mapping enhances catheter robots in endovascular procedures, ensuring precise navigation and stent delivery [3]. Challenges stem from non-linear dynamics and external loads, demanding precision, robustness, and real-time performance.

Traditional kinematic models struggle with computational complexity and adaptability to dynamic settings [4], [5]. Neural network-based approaches excel in capturing non-linearities, but often lack closed-loop consistency under load variations [6]. Submillimeter precision and millisecond latency are critical for real-time control in surgical and industrial uses.

We propose a cycle-consistent neural network framework combining a CNN-based encoder-decoder for force-to-position mapping with a KAN-based model for position-to-force mapping. A hybrid training approach—separate training and joint fine-tuning with cycle consistency loss—ensures physical consistency across loads. In a tendon-driven continuum robot dataset to simulate surgical scenarios, our model delivers high precision (forward MSE: 0.000148 m^2 no load, 0.000337 m^2 with load; inverse MSE: 0.0098 N^2 no-load, 0.0376 N^2 with load) and low cycle errors (0.000217–0.000346 m^2), with prediction times of 0.15–0.25 ms/sample, enabling real-time control.

Fig. 1 shows the robot driven by tendons, Fig. 2 shows the network architecture, and Fig. 3 compares the performance metrics. This paper explores the implications for the implications for the methodolcontrol.control.

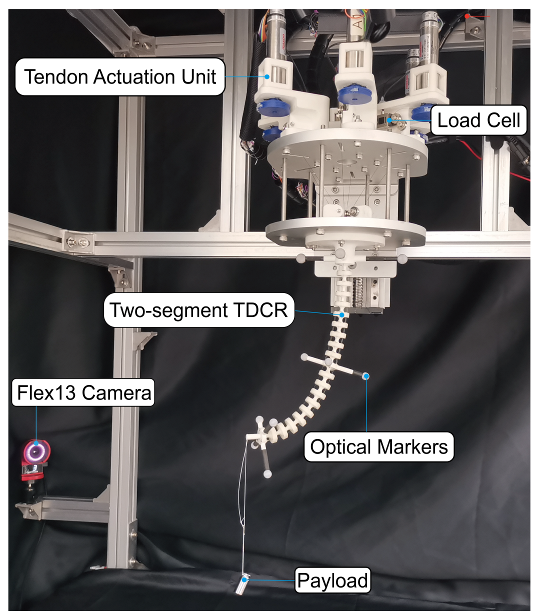

Fig. 1. Tendon-driven continuum robot used in experiments.

II. Methodology and Results

We propose a cycle-consistent neural network framework for force-position mapping in tendon-driven surgical soft robot, as shown in Fig. 2. The forward model, a CNN-based encoder-decoder, maps 7-dimensional inputs (six tendon forces and one payload weight) to 6-dimensional positions

*Corresponding author: Xin Xu

[1]Yang Song, Bowen Su, Wendi Liang and Xin Xu are with the Department of Mechanical Engineering, Hong Kong Polytechnic University, Hong Kong, SAR, China (e-mail: 20116167r@connect.polyu.hk, saber.su@connect.polyu.hk; wendi.liang@connect.polyu.hk, xin-21.xu@connect.polyu.hk).

[2]Di Wu is with the Maersk Mc-Kinney Moller Institute, University of Southern Denmark, 5230, Odense, Denmark (e-mail: diwu@mmmi.sdu.dk).

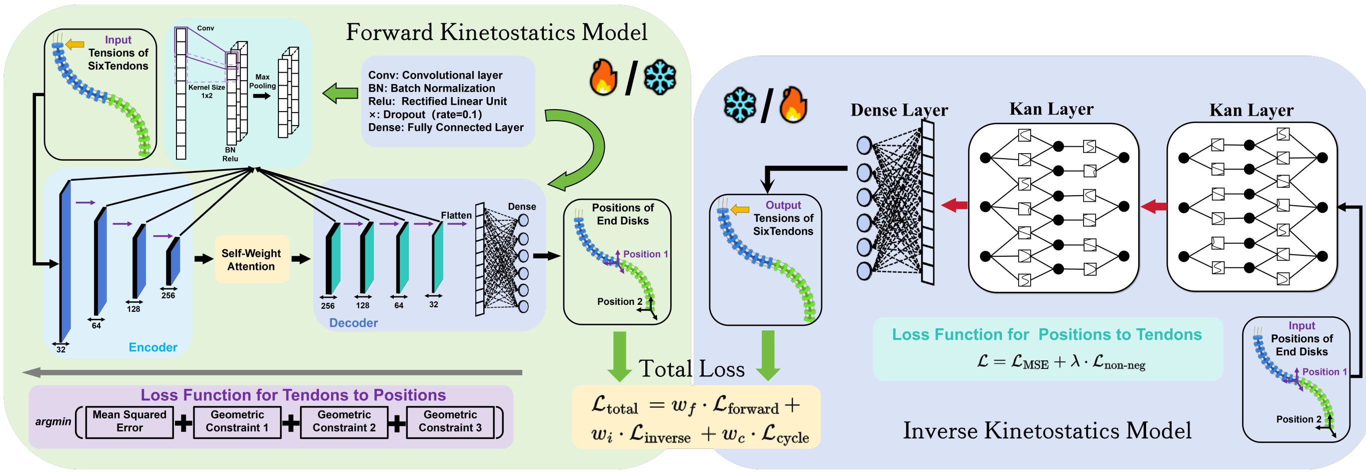

Fig. 2. Proposed model architecture.

using convolutional layers and attention. The inverse model, a KAN-based network, performs the kinetostatic mapping from positions to forces with two KAN layers and residual connections for non-negative forces. A mixed training strategy—separate training (300 epochs each) and joint fine-tuning (200 epochs) with Adam optimization—is employed. Losses include MSE with distance penalties (forward), non-negative penalties (inverse), and cycle consistency:

$$\mathcal{L}_{\text{cycle}} = \frac{1}{N \cdot 6} \sum_{i=1}^{N} \sum_{j=1}^{6} \left(y_{\text{true},i,j} - y_{\text{recovered},i,j} \right)^2 ,$$

where $\mathbf{y}_{\text{recovered}} = f_{\text{forward}}(f_{\text{inverse}}(\mathbf{y}_{\text{true}}))$.

Evaluated on a dataset (80% training, 20% testing, MinMaxScaler), the model achieves high precision without load (forward MSE: 0.000148 m^2; inverse MSE: 0.0098 N^2; cycle error: 0.000217 m^2) and robust performance with load (forward MSE: 0.000337 m^2; inverse MSE: 0.0376 N^2; cycle error: 0.000347 m^2), as shown in Fig. 3. Prediction times (0.15–0.25 ms/sample) support real-time control.

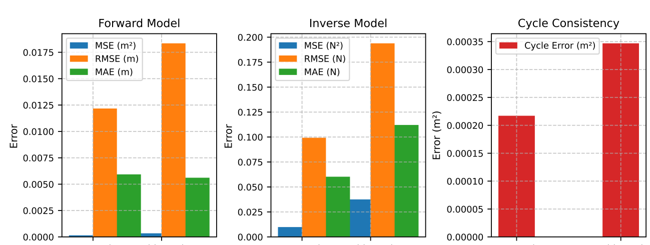

Fig. 3. Performance metrics for tendon-driven Surgical Soft Robot.

III. Conclusion

This research introduces a framework based on a cycle-consistent neural network aimed at accurately mapping force to position in tendon-driven surgical soft robot, achieving both high precision and real-time control. The framework incorporates a CNN-based forward model alongside a KAN-based inverse model for kinetostatic mapping, ensuring closed-loop consistency through a hybrid training approach. Experimental findings reveal strong performance, evidenced by forward mean squared errors (MSEs) of 0.000148 m^2 under no-load conditions and 0.000337 m^2 under load, as well as inverse MSEs of 0.0098 N^2 and 0.0376 N^2, with cycle errors ranging from 0.000217 to 0.000347 m^2. The model demonstrates prediction times between 0.15 and 0.25 ms per sample, supporting its application in fields such as surgery and navigation.

Nonetheless, the presence of load-induced errors in the inverse kinetostatic model indicates the need for future efforts to improve adaptability to dynamic environments and multi-robot systems.

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