

# Learning-Based Modeling of Soft Actuators Using Euler Spiral-Inspired Curvature

Yu Mei, Shangyuan Yuan, Xinda Qi, Preston Fairchild and Xiaobo Tan

Department of Electrical and Computer Engineering  
Michigan State University

Oct 06, 2025

MECC 2025



# Background of Soft Robots

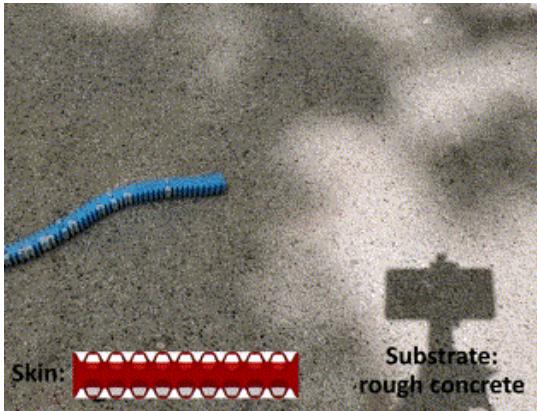


Figure: Soft snake robot <sup>1</sup>

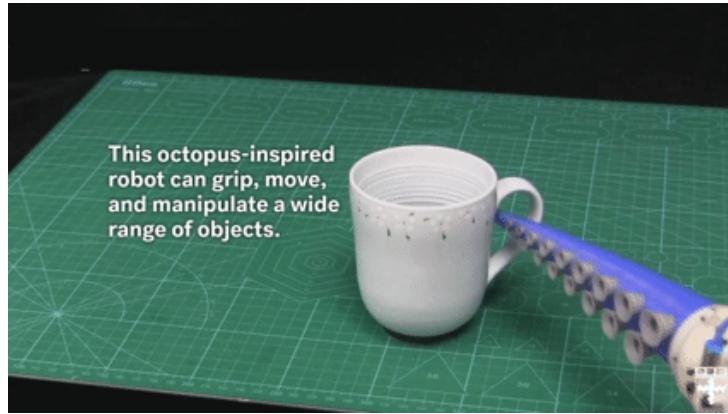


Figure: Octopus-inspired gripper <sup>2</sup>

## Challenges

- Infinite degrees of freedom
- Actuation physics
- Environmental interaction

## Categories of Modeling

- Piecewise constant curvature approach (PCC)
- Variable curvature approach (VC)

<sup>1</sup> Qi et al., Soft Robotics '18

<sup>2</sup> Xie et al., Soft Robotics '20

# Piecewise Constant Curvature approach (PCC)

## □ PCC examples

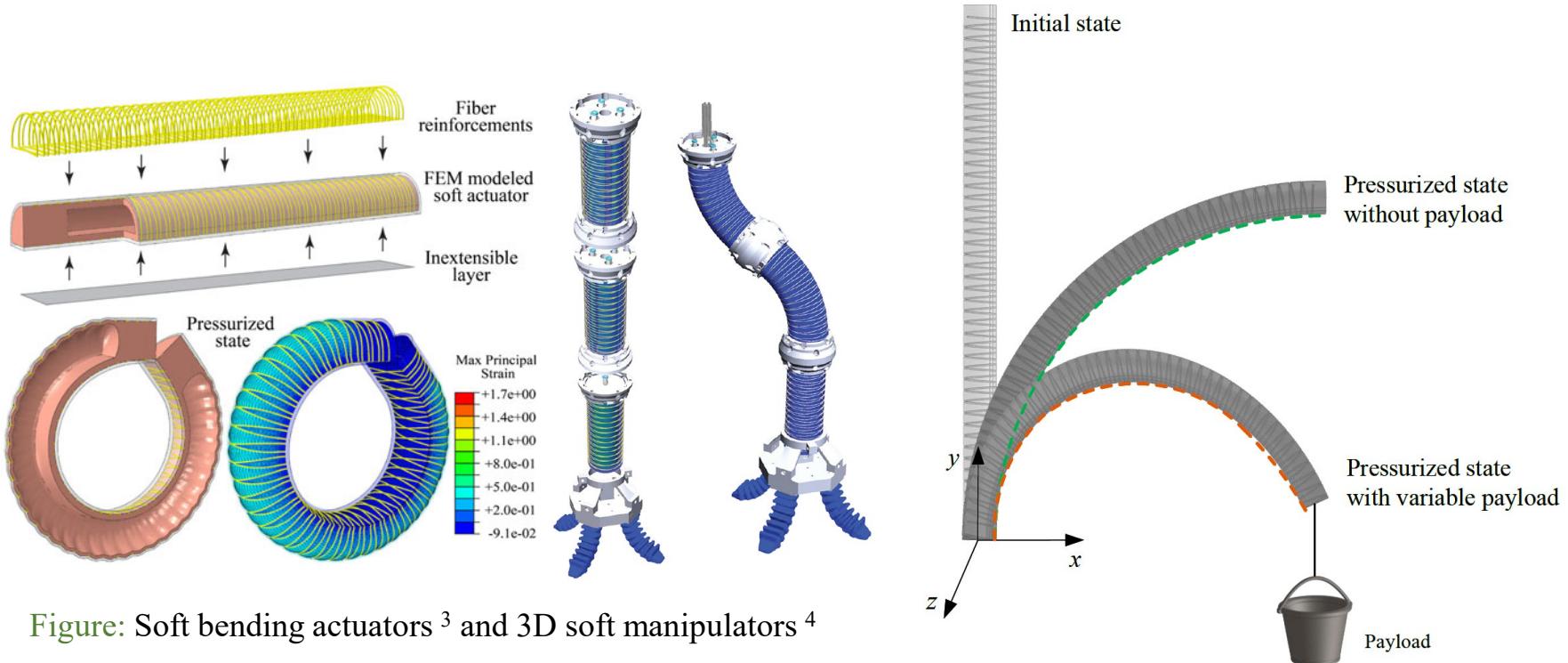


Figure: Soft bending actuators<sup>3</sup> and 3D soft manipulators<sup>4</sup>

## Limitation

It fails to capture the shape under relatively large payloads or gravity.

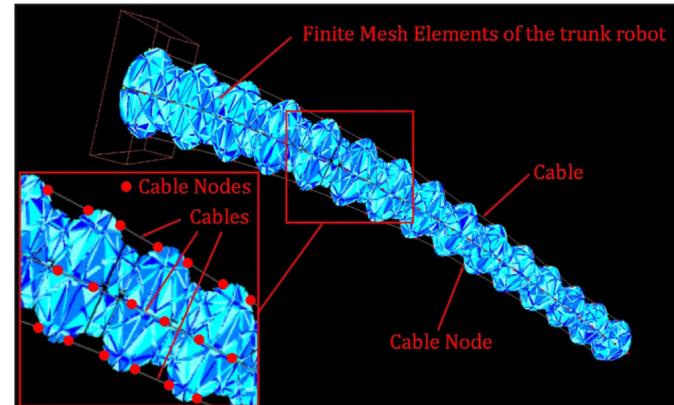
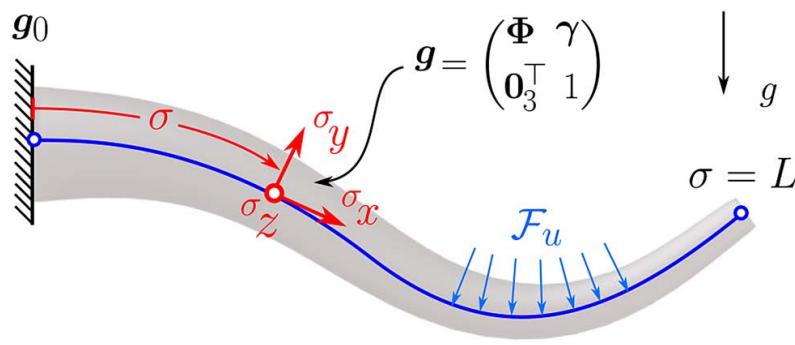
<sup>3</sup> Polygerinos et al., TRO '18

<sup>4</sup> Gong et al., IJRR '20

# Variable Curvature approach (VC)

## VC approaches

- ❑ Cosserat rod theory [Renda, TRO '18]
- ❑ Finite element method (FEM) [Wu, RAL '22]



Limitation: **High computational cost** due to PDEs or large sets of coupled ODEs

## Goal

**Compact** VC representation but still captures **continuous** shape with **high-fidelity**.

# Overview

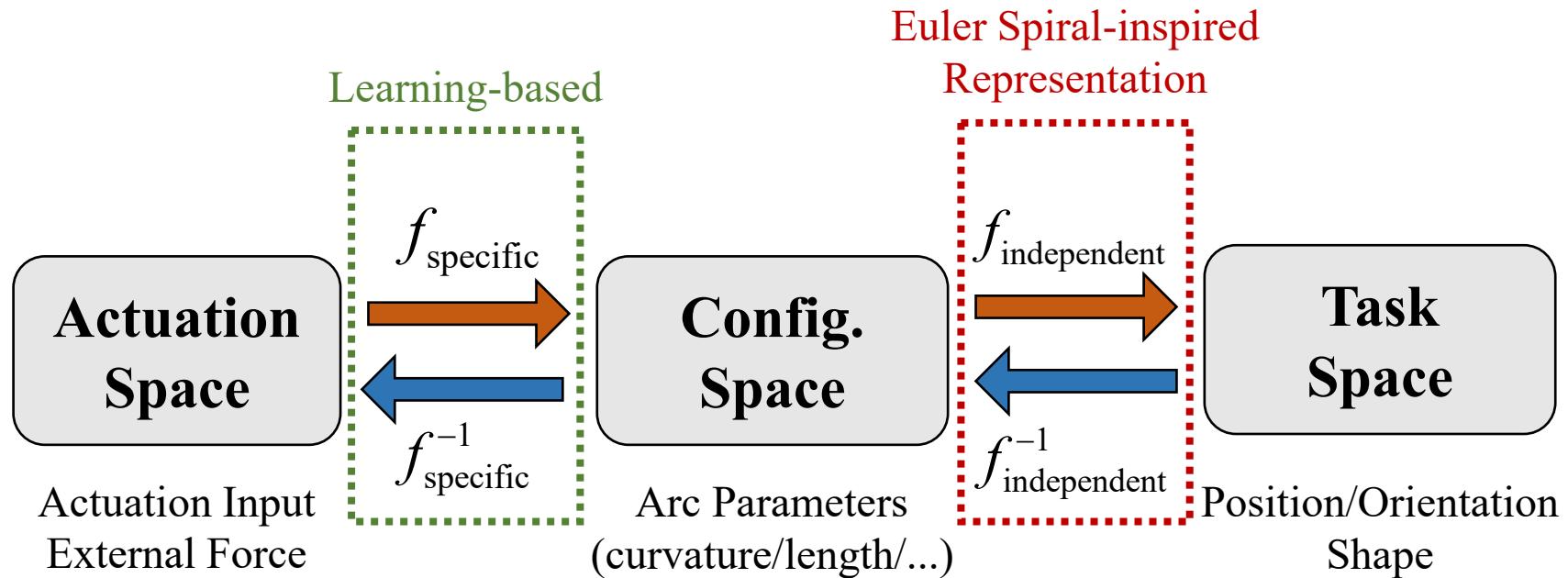


Figure: General framework of modeling for soft robots <sup>5</sup>

<sup>5</sup> Webster et al., IJRR '10

# Euler Spiral

## Definition

- Proposed in 1694 by Bernoulli as the classic elastica problem.
- The curvature changes linearly with respect to the arc length.

## Applications

- Rail track transition design<sup>6</sup>
- Shape completion<sup>7</sup>



<sup>6</sup>Eliou et al., Eur. Transp. Res. Rev. '14;

<sup>7</sup>He et al., Vis. Comput. Ind. Biomed. Art. '21.

# Shape Representation inspired by Euler Spiral

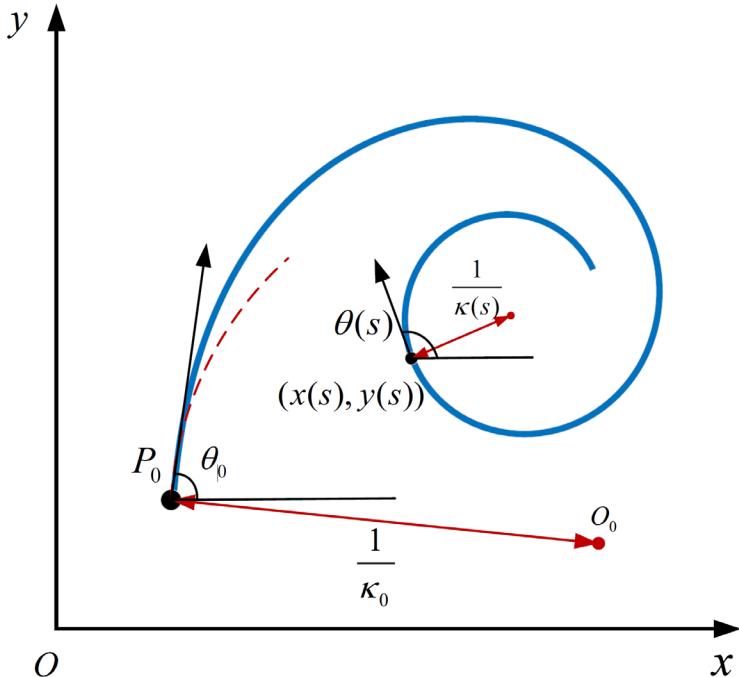


Figure: Illustration of the Euler Spiral

$$\begin{cases} \dot{x}(s) = \cos \theta(s), & x(0) = x_0, \\ \dot{y}(s) = \sin \theta(s), & y(0) = y_0, \\ \dot{\theta}(s) = \kappa(s), & \theta(0) = \theta_0, \end{cases} \quad (1)$$

Traditional:  $\kappa(s) = \kappa_1 s + \kappa_0,$

Extended:  $\kappa(s) = \sum_{k=0}^N \kappa_k s^k,$  (2)

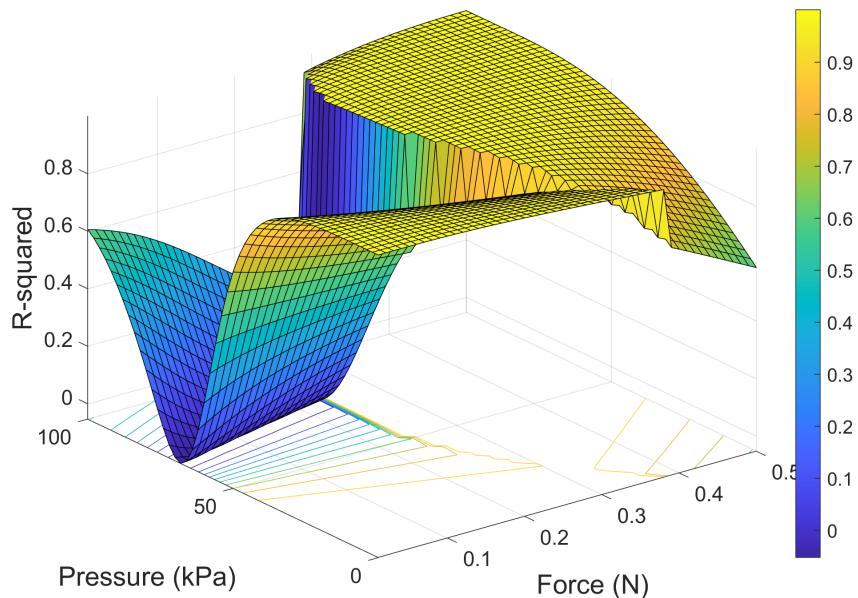
By plugging Eq. (2) into Eq. (1), one can get:

$$\begin{cases} x(s) = \int_0^s \cos(\theta(\tau)) d\tau + x_0, \\ y(s) = \int_0^s \sin(\theta(\tau)) d\tau + y_0, \\ \theta(s) = \sum_{k=0}^N \frac{\kappa_k}{k+1} s^{k+1} + \theta_0, \end{cases} \quad (3)$$

The curve is compactly characterized by the shape parameters  $\mathbf{q} = \{\kappa_k\} = [\kappa_0, \kappa_1, \dots, \kappa_N]^T.$

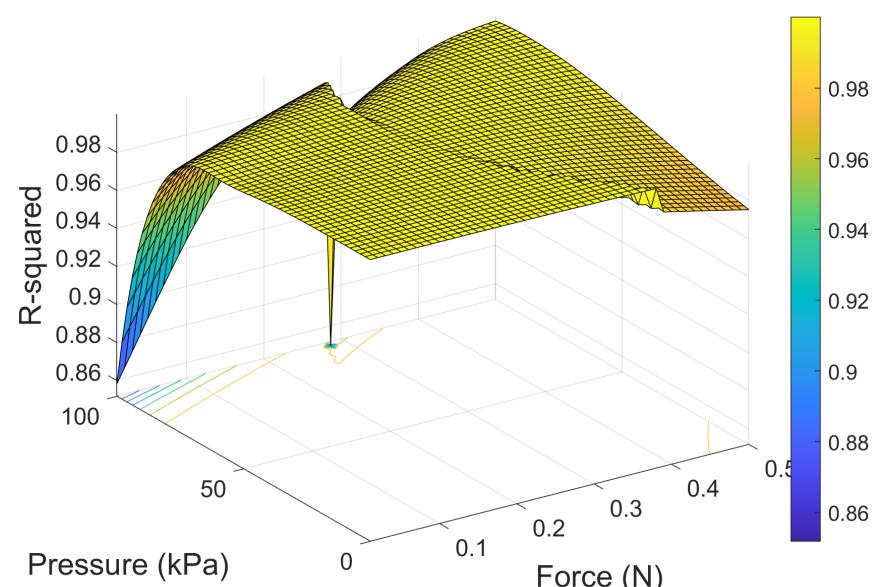
# Numerical Validation

- High-fidelity physical simulation for soft bending actuator (ground truth)<sup>7</sup>
- Validation Results (curve fitting)



Traditional Euler Spiral with first order:

$$R^2 = 0.77 \pm 0.31$$

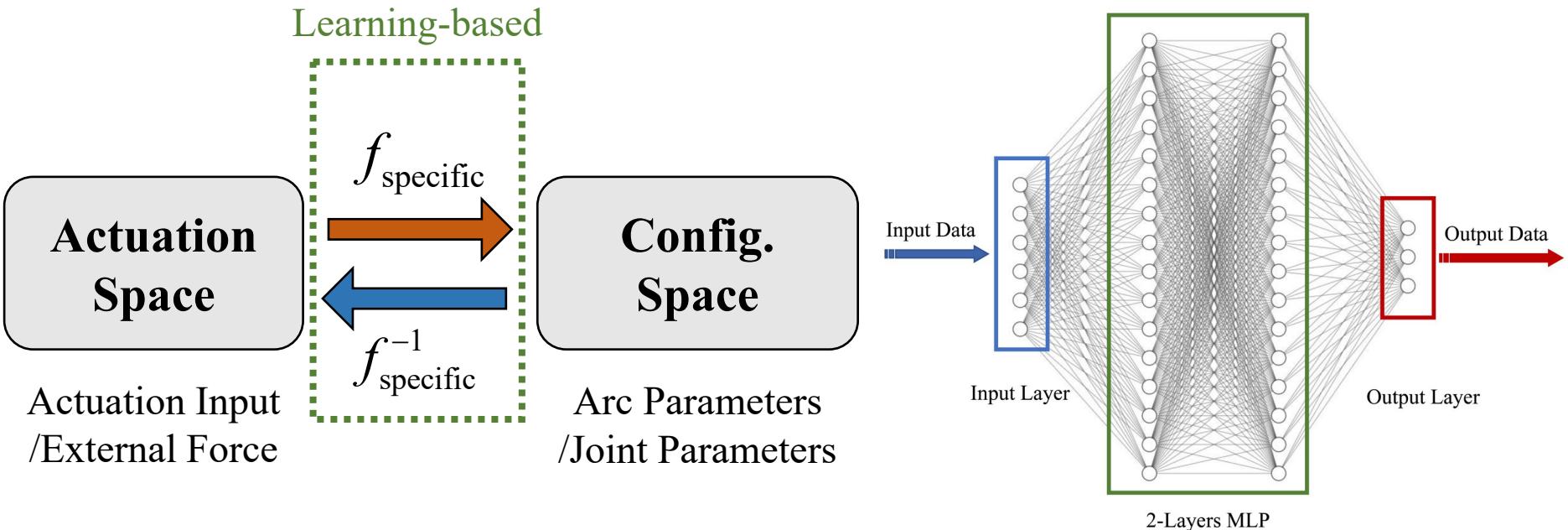


Quadratic Euler Spiral with second order:

$$R^2 = 0.99 \pm 0.01$$

<sup>7</sup> Mei et al., TMech '24

# Learning-based Forward and Inverse Models



- Actuation input for this specific robot: Pneumatic input  $P$ , Payload  $W$ .
- Forward neural network: Input is  $[P, W]^T$  and output is  $\mathbf{q} = \mathbf{\kappa}^T$ .
- Inverse neural network: Input is  $[\mathbf{q}, P]^T$  and output is  $W$ .

Dataset collection:  $[P, W, \mathbf{q}]$

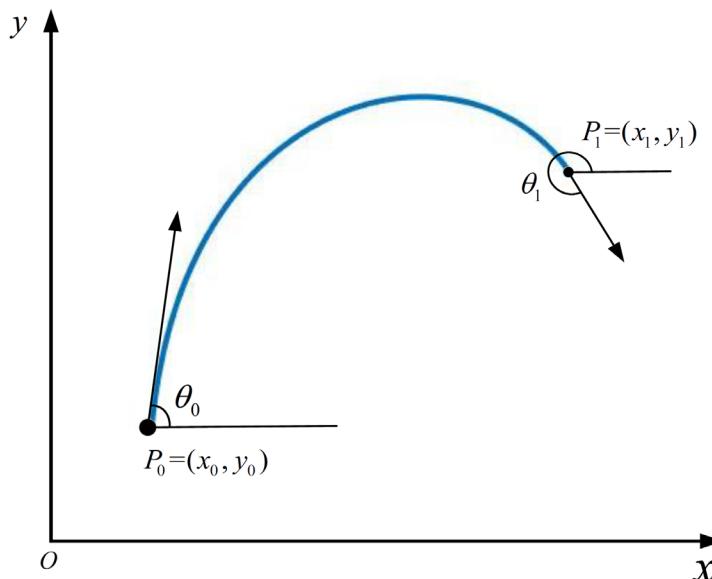
# Curvature Parameters Extraction

## Challenge of Dataset Collection

The direct and accurate measurement of the curvature is not readily available.

## G<sup>1</sup> Hermite Interpolation Problem

Finding a G<sup>1</sup> smooth curve fitting two given points  $P_0, P_1$  and the corresponding orientation angles  $\theta_0, \theta_1$ .



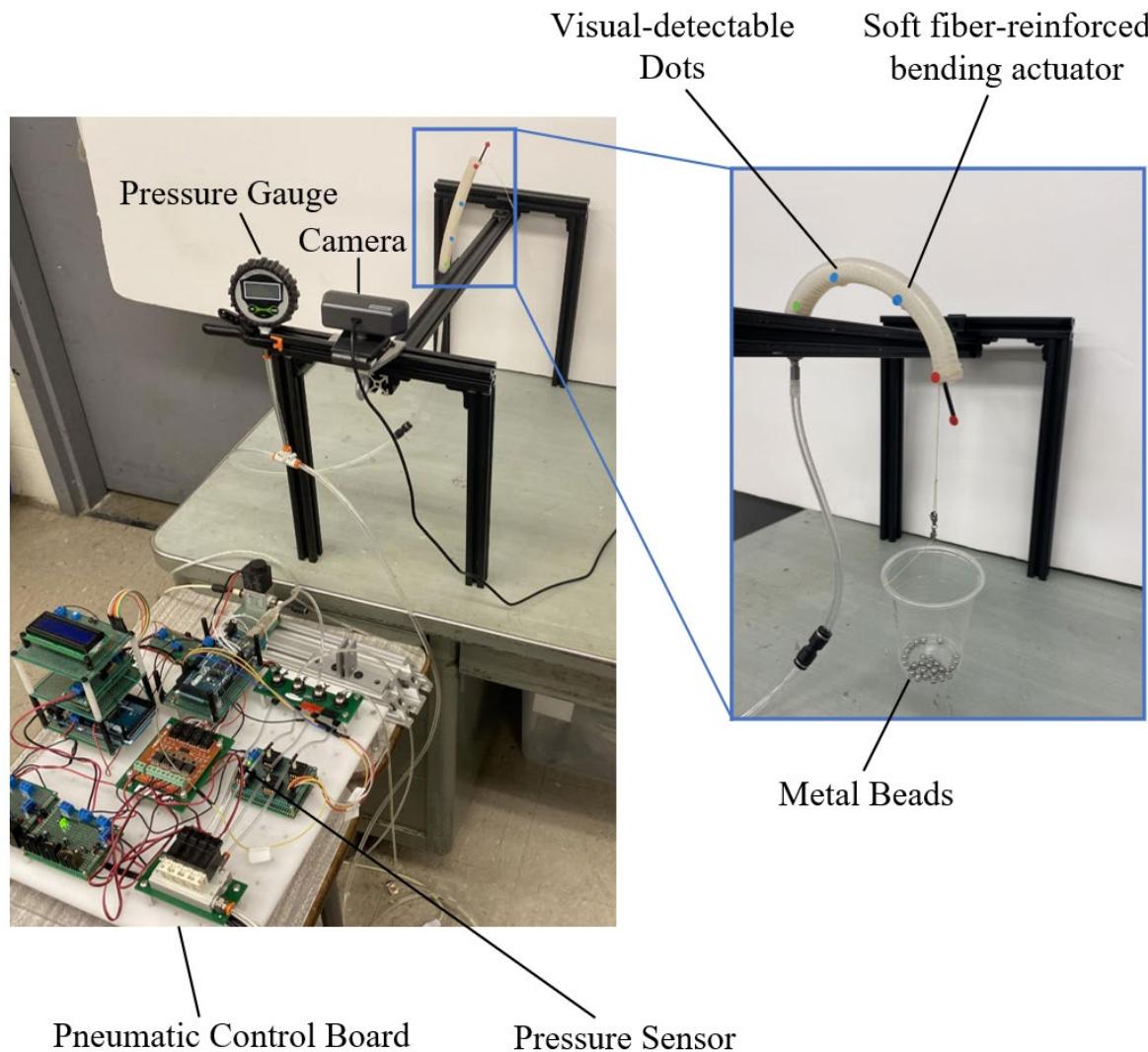
Optimization Problem:

$$\kappa^* = \arg \min_{\kappa \in \mathbb{R}^{N+1}} \left\| \begin{bmatrix} x(L; \kappa) - x_1 \\ y(L; \kappa) - y_1 \\ \theta(L; \kappa) - \theta_1 \end{bmatrix} \right\|_2^2$$

$$\text{s.t. } x(0) = x_0, \quad y(0) = y_0, \\ \dot{x}(0) = \cos \theta_0, \quad \dot{y}(0) = \sin \theta_0,$$

Figure: Illustration of G1 Hermite Interpolation

# Experimental Setup



# Model Prediction Results

## □ Forward Model Prediction Results

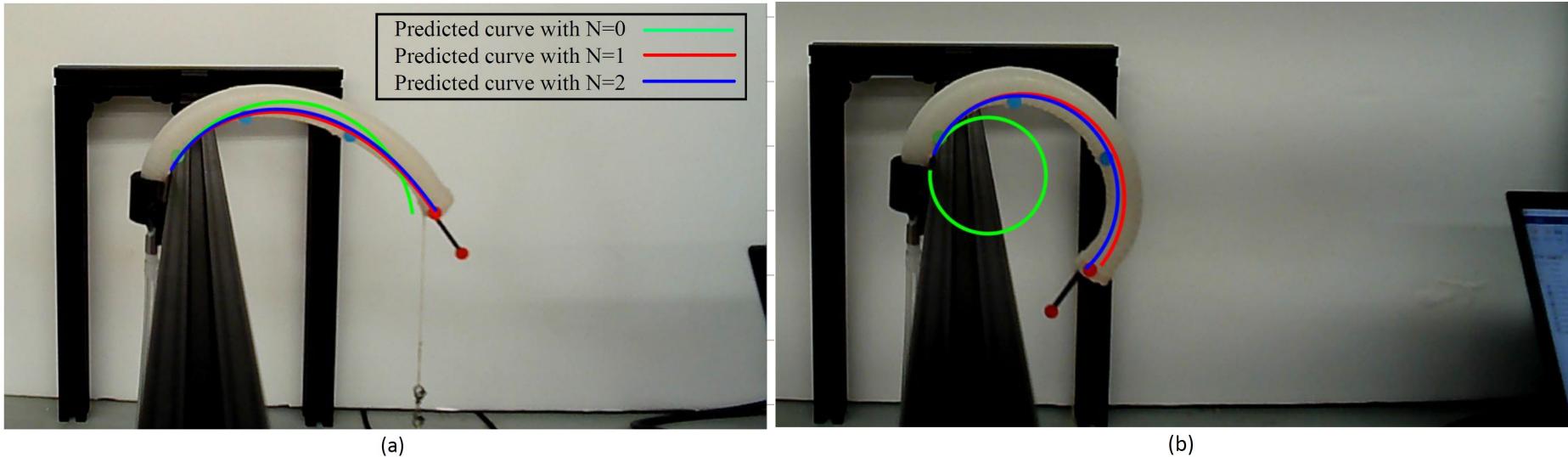


Table I. Average errors (%) at three reference points relative to actuator length.

	1/3 position error (%)	2/3 position error (%)	Tip error (%)
N=2	$3.38 \pm 0.21$	$2.19 \pm 0.40$	$1.93 \pm 1.33$
N=1	$3.43 \pm 0.18$	$2.50 \pm 0.45$	$2.02 \pm 1.58$
N=0	$6.67 \pm 4.24$	$17.5 \pm 19.0$	$35.0 \pm 35.0$

# Model Prediction Results

## □ Inverse Model Prediction Results

Table II. Average tipload errors (%) with respect to the range of the payload for different orders.

Order	Load Error (%)
$N = 2$	$0.72 \pm 0.62$
$N = 1$	$1.08 \pm 1.12$
$N = 0$	$1.21 \pm 1.08$

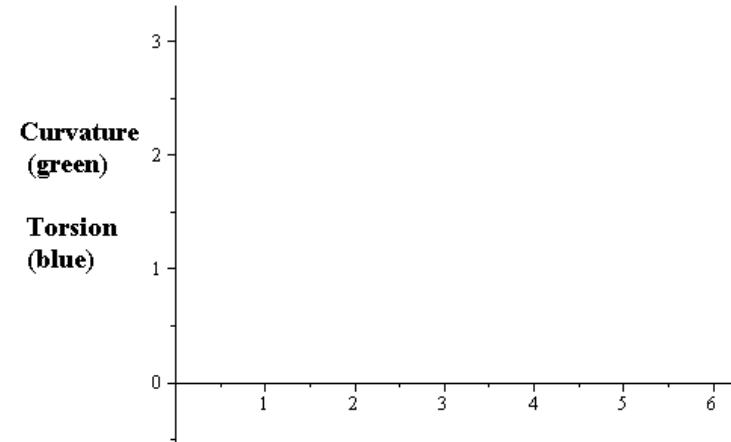
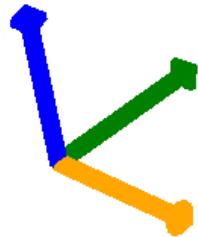
Payload resolution is 0.254g for each bead (1%)

# Conclusions

1. A **compact** VC representation but captures **continuous** shape with **high-fidelity**
2. Effective curvature extraction using  $G^1$  Hermite interpolation
3. Learning-based model for robot-specific mapping
4. Experimental validations on actual robot

# Future Work

1. Control-oriented dynamic model
2. Extend to 3D space with torsion



## Acknowledgements:

This research was supported in part by National Science Foundation awards (CNS 2237577, ECCS 2024649 and CMMI 1940950).



# Thank you!

# Reference

1. X. Qi, T. Gao, and X. Tan, “Bioinspired 3D-Printed Snakeskins Enable Effective Serpentine Locomotion of a Soft Robotic Snake,” *Soft Robotics*, p. soro.2022.0051, Nov. 2022.
2. Z. Xie, W. Li *et al.*, “Octopus Arm-Inspired Tapered Soft Actuators with Suckers for Improved Grasping,” *Soft Robotics*, vol. 7, no. 5, pp. 639–648, Oct. 2020.
3. P. Polygerinos *et al.*, “Modeling of Soft Fiber-Reinforced Bending Actuators,” *IEEE Transactions on Robotics*, vol. 31, no. 3, pp. 778–789, Jun. 2015.
4. Z. Gong *et al.*, “A soft manipulator for efficient delicate grasping in shallow water: Modeling, control, and real-world experiments,” *The International Journal of Robotics Research*, vol. 40, no. 1, pp. 449–469, Jan. 2021.
5. B. Caasenbrood, A. Pogromsky, and H. Nijmeijer, “Energy-Shaping Controllers for Soft Robot Manipulators Through Port-Hamiltonian Cosserat Models,” *SN COMPUT. SCI.*, vol. 3, no. 6, p. 494, Sep. 2022.
6. K. Wu, G. Zheng, and J. Zhang, “FEM-based trajectory tracking control of a soft trunk robot,” *Robotics and Autonomous Systems*, vol. 150, p. 103961, Apr. 2022.
7. S. Sadati *et al.*, “Reduced Order vs. Discretized Lumped System Models with Absolute and Relative States for Continuum Manipulators,” in *Robotics: Science and Systems XV*, Robotics: Science and Systems Foundation, Jun. 2019.
8. R. J. Webster and B. A. Jones, “Design and Kinematic Modeling of Constant Curvature Continuum Robots: A Review,” *The International Journal of Robotics Research*, vol. 29, no. 13, pp. 1661–1683, Nov. 2010.
9. R. Levien, “The Euler spiral: a mathematical history”, 2008.
10. N. Eliou and G. Kaliabetsos, “A new, simple and accurate transition curve type, for use in road and railway alignment design,” *Eur. Transp. Res. Rev.*, vol. 6, no. 2, pp. 171–179, Jun. 2014.
11. C. He, G. Zhao, A. Wang, F. Hou, Z. Cai, and S. Li, “Typical curve with G1 constraints for curve completion,” *Vis. Comput. Ind. Biomed. Art*, vol. 4, no. 1, p. 28, Dec. 2021.
12. P. Rao, Q. Peyron, and J. Burgner-Kahrs, “Using Euler Curves to Model Continuum Robots,” in 2021 IEEE International Conference on Robotics and Automation (ICRA), May 2021, pp. 1402–1408.
13. Y. Mei *et al.*, “Simultaneous Shape Reconstruction and Force Estimation of Soft Bending Actuators Using Distributed Inductive Curvature Sensors,” *IEEE/ASME Trans. Mechatron.*, pp. 1–9, 2024.