NRI: FND: Bioinspired Design and Shared Autonomy for Underwater Robots with Soft Limbs

Award Number 1734627

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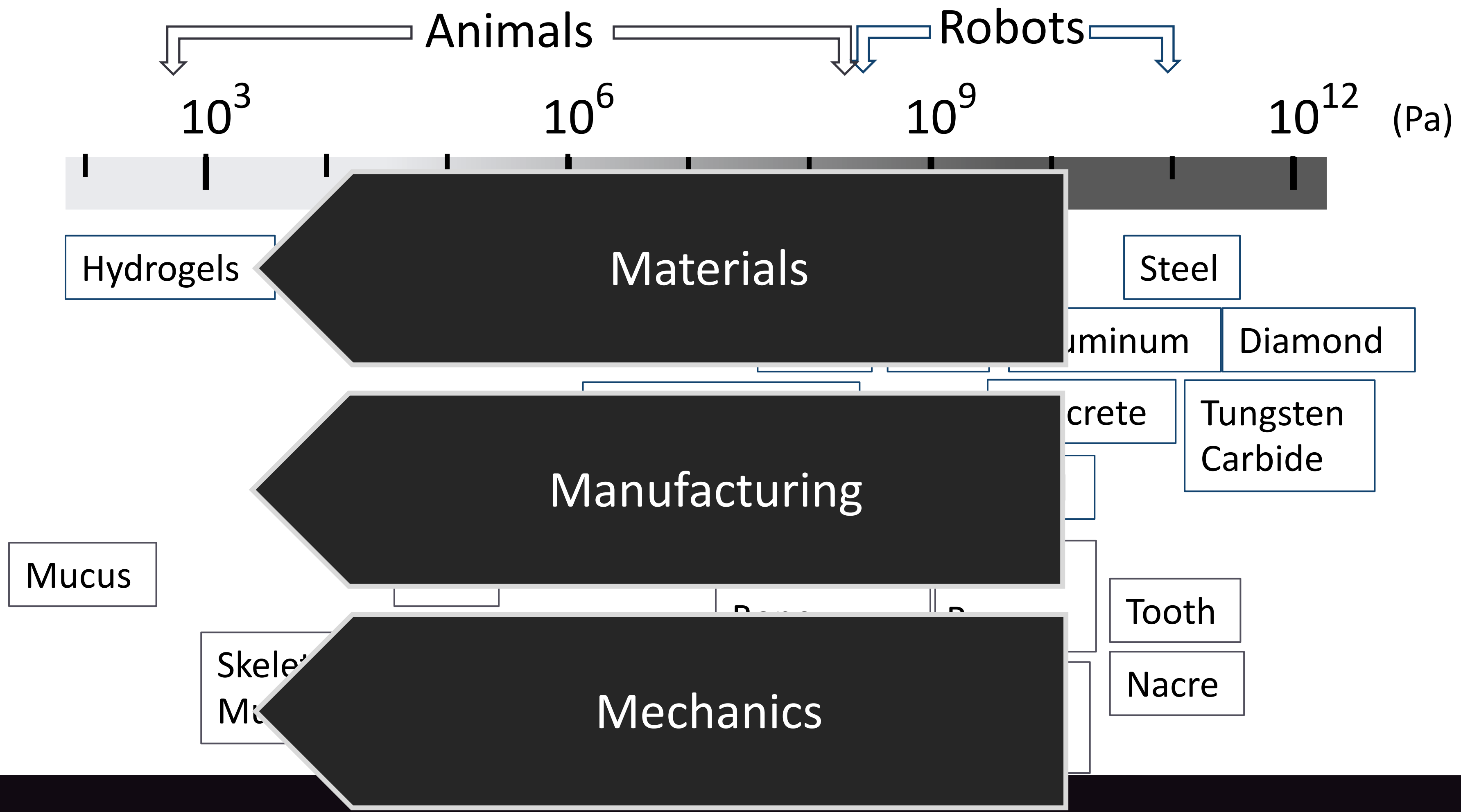
mLab Robotics

Oregon State University

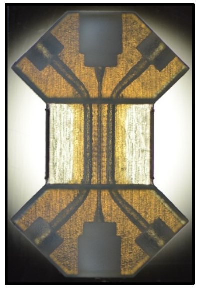
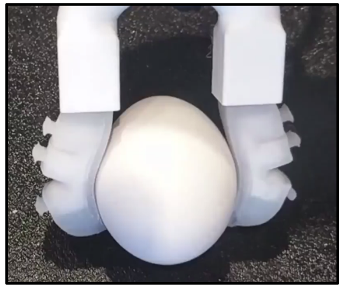
Philosophy:
Technology Within a Spectrum of Softness



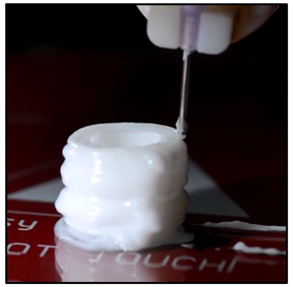
Progress Timeline

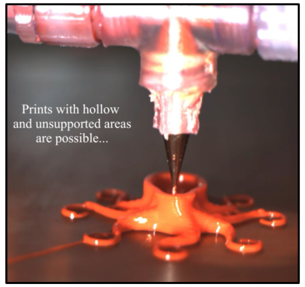
2016 | 2017 | 2018 | 2019

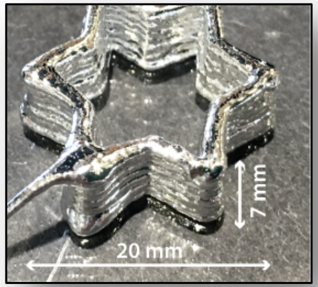
Materials

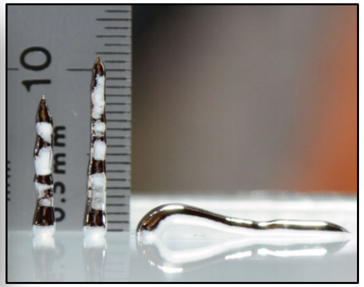
   

Manufacturing

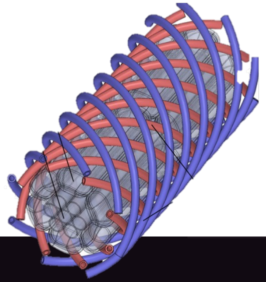
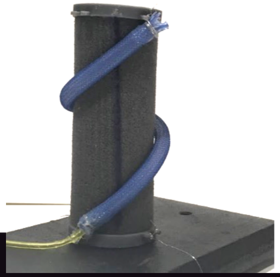








Mechanics

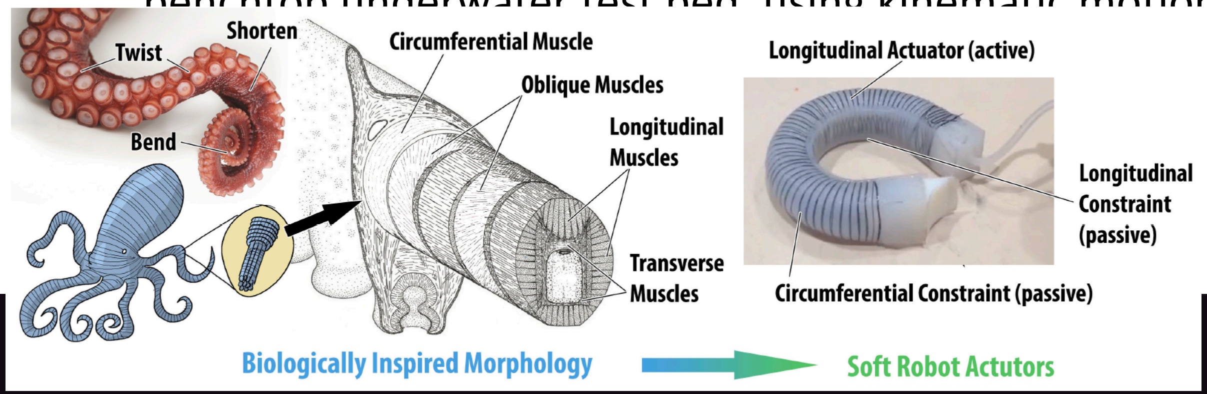
   

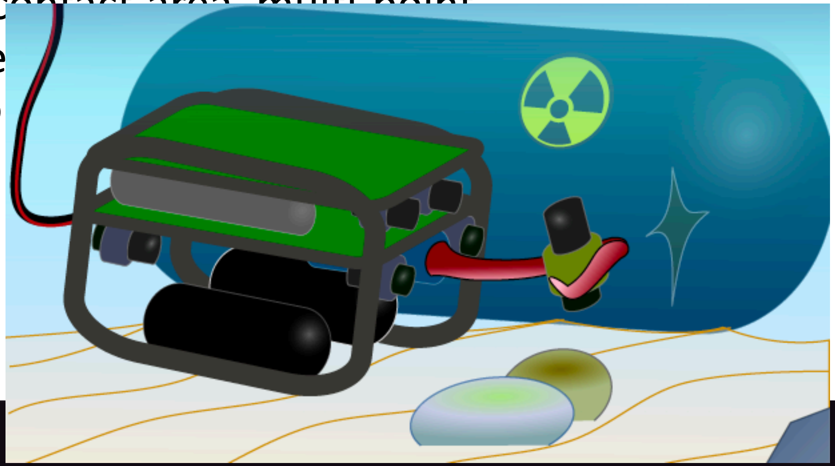
Outline

- Soft Simulation and Planning
- Learning Load States
- Generalizable Mechanical Models (Gina Olson)

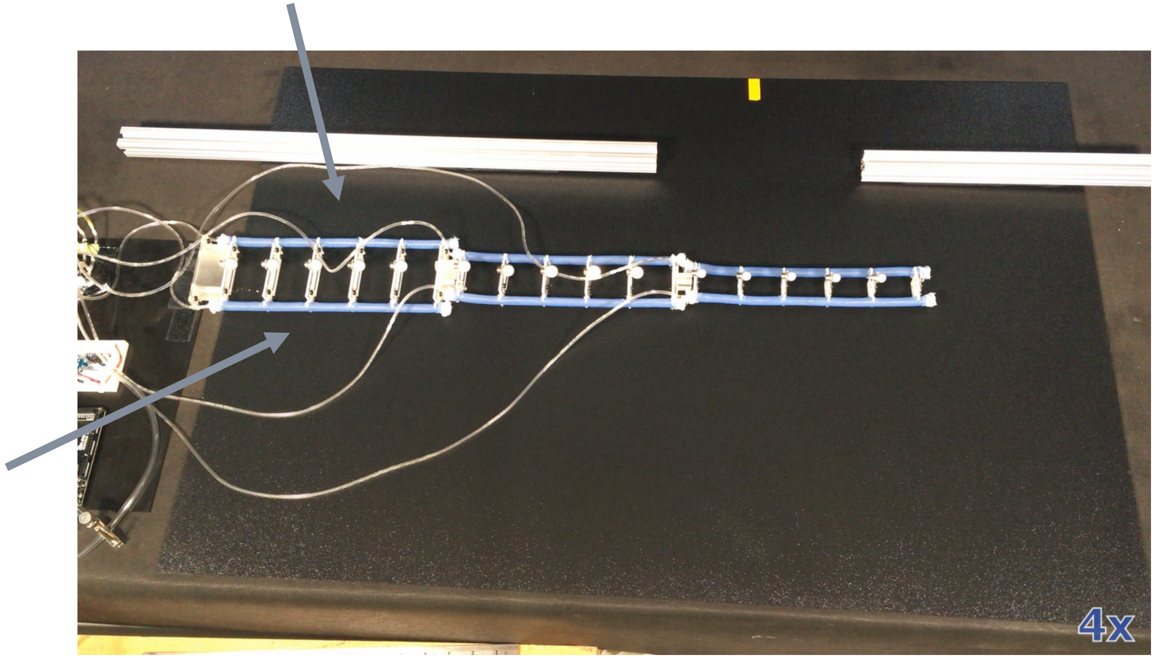
Currently, delicate and challenging underwater manipulation tasks are performed only by human divers when it is safe for them to enter the environment. Robots can help address this issue by distancing human operators from dangerous environments, while still leveraging their skills in planning complex manipulation tasks. Rigid robotic manipulators, however, are typically not suitable for delicate manipulation tasks. To address this limitation, this project explores the design and control of soft robotic arms inspired by the octopus.

The objective of this research is to establish a framework for underwater manipulation, combining shared autonomy between human operators and robots with mechanically-directed soft actuation and sensing. The proposed work will examine new actuator morphologies, alternative fabrications techniques, and the use of stretchable integrated liquid metal sensors. To control the soft grippers, this project develops a planning and control interface that utilizes machine learning techniques to leverage human operators' skills at quickly identifying stable grasps. The physical attributes of the soft grippers will be designed in tandem with algorithms, which will provide improved understanding of underwater interaction and shared autonomy. Dexterity and compliance of the soft manipulators will be evaluated for large contact area, multi-point gripping, which is particularly advantageous for grasping delicate objects unde
benchtop underwater test bed, using kinematic motion capture and interactio





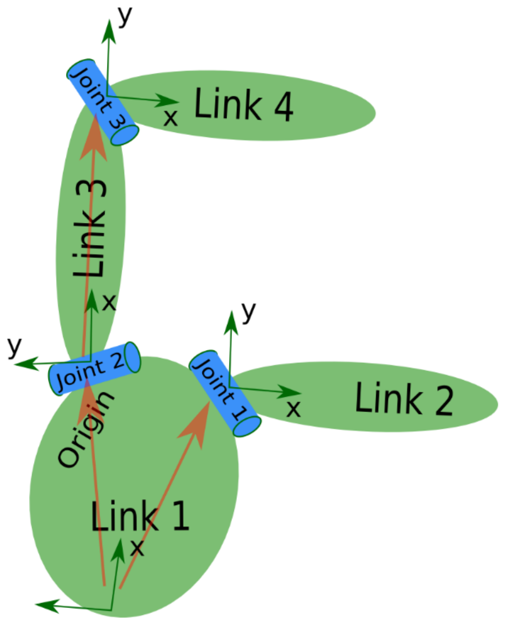
What we want to simulate

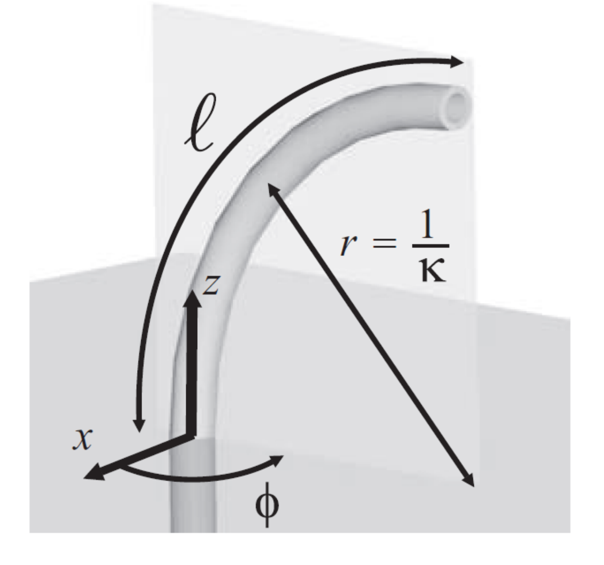


- Pairs of pneumatic actuators
- Inflation causes contraction
- Planar arrangement

Why an In-House Simulator?

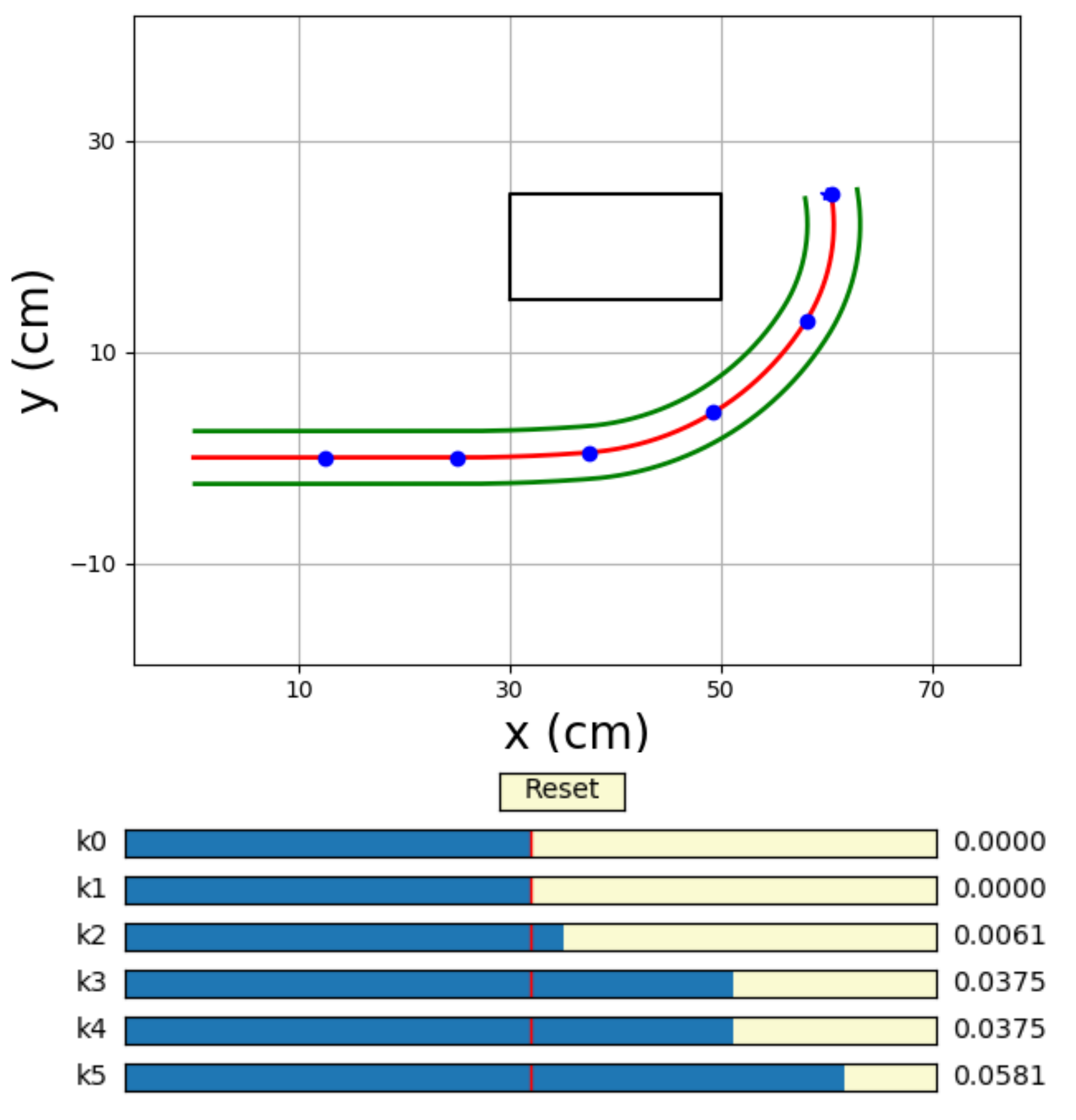
- Simulators such as Gazebo assume robots are defined by links and joints
- Modeling piecewise constant curvature as a chain of links and joints decreases accuracy
- Overhead for physics that we can not utilize





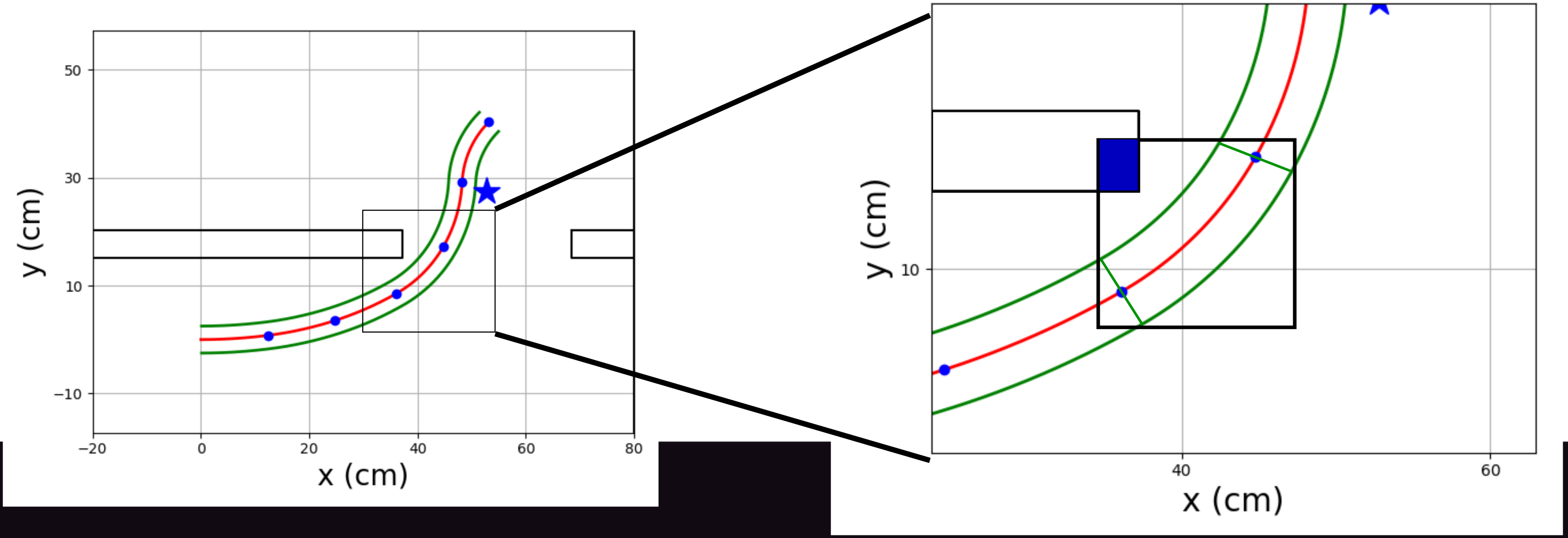
SoftSim: A Kinematic Simulator for Soft Robots

- Support any number of segments
- Computes forward kinematics
    - Shape and tip position of the arm
- Support for environment with obstacles and collision detection
- Manual control via sliders or automatic control



SoftSim: Collision Detection

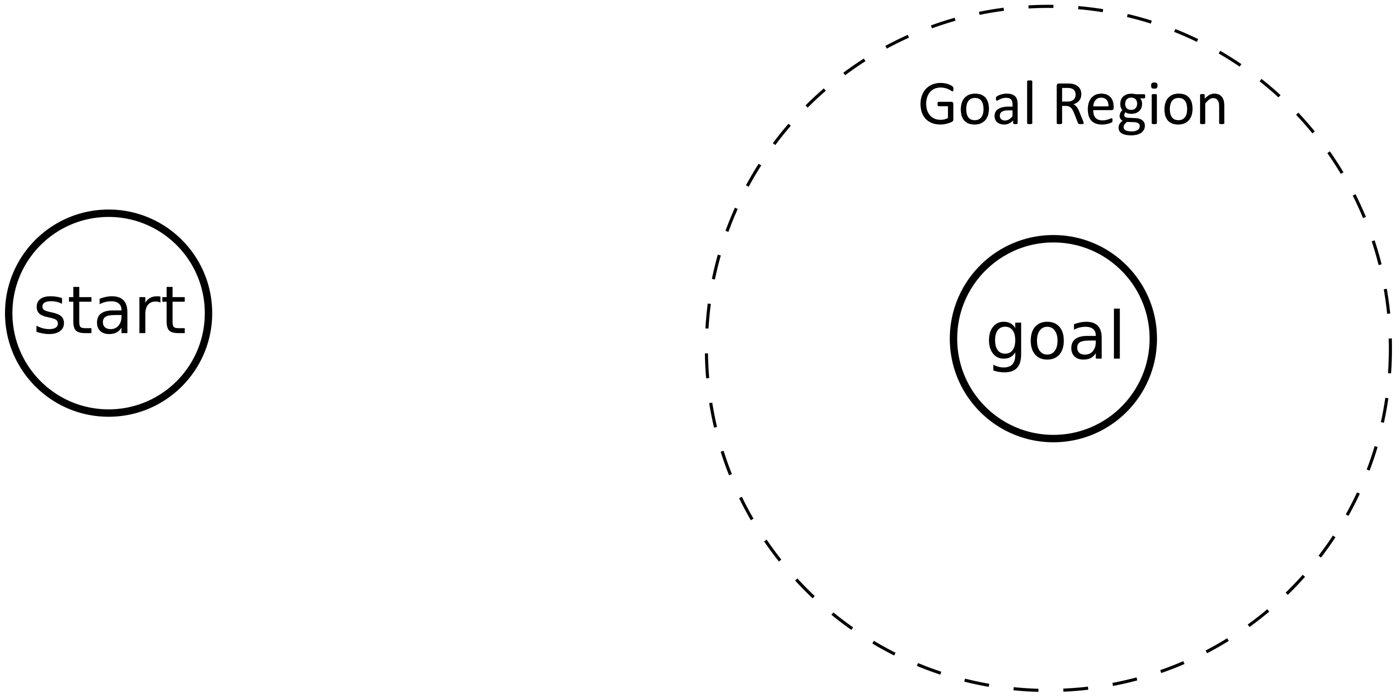
- Standard approach: Circular Arc-Line intersection test with bounds
  - Precise but slower to compute compared to…
- Axis-Aligned Bounding Boxes (AABB)
  - Fast but chance of false positive

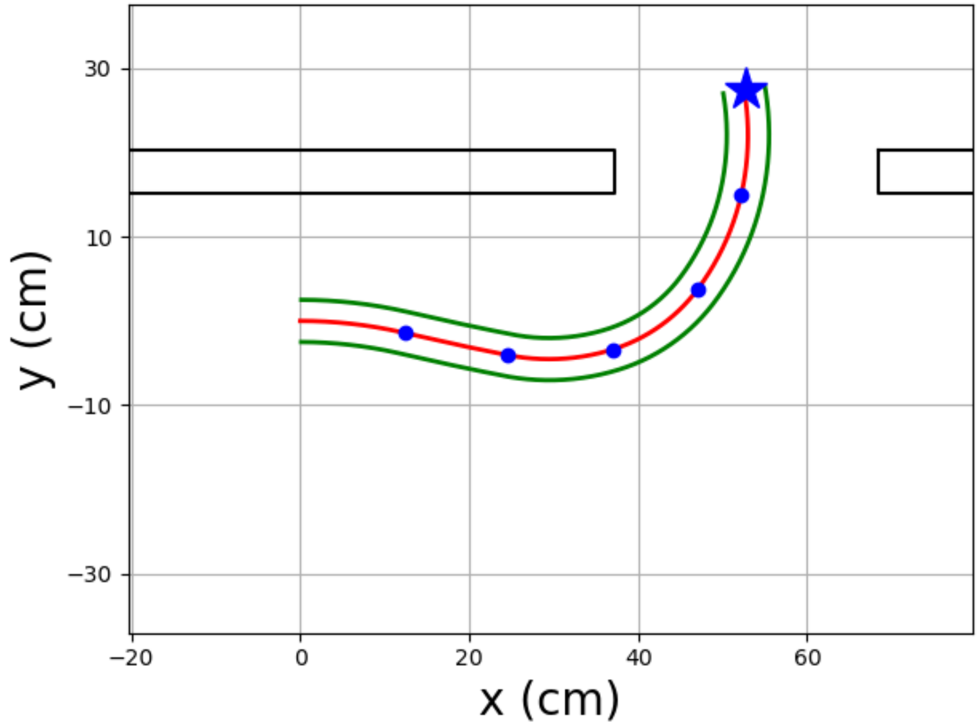


SoftSim: Collision Detection

- Standard approach: Circular Arc-Line intersection test with bounds
  - Precise but slower to compute compared to…
- Axis-Aligned Bounding Boxes (AABB)
  - Fast but chance of false positive
- Our Approach:
  - Use AABB to rule out clearly non-collision cases
  - Use Circular Arc-Line intersection last

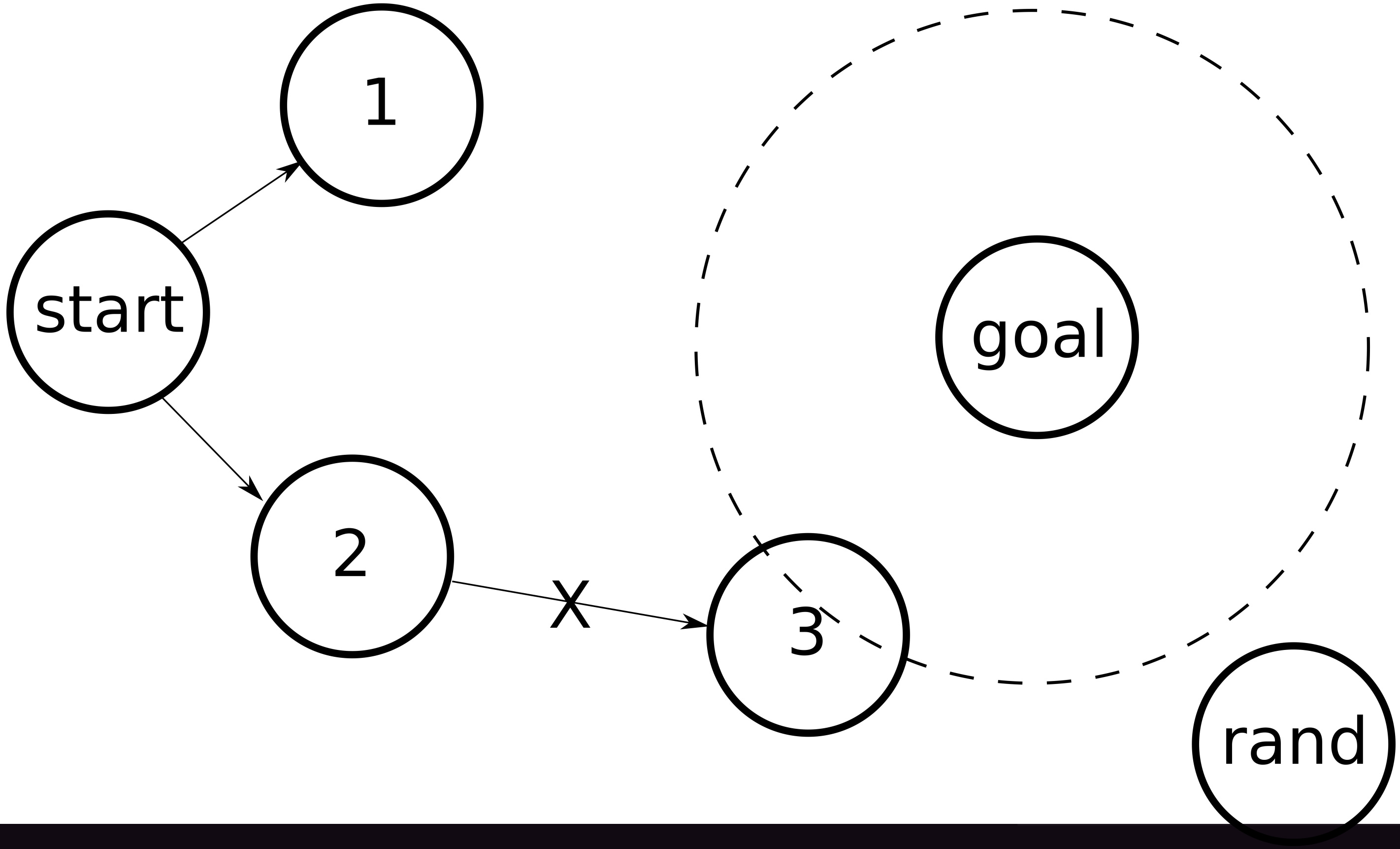
Background: Rapidly-Exploring Random Trees

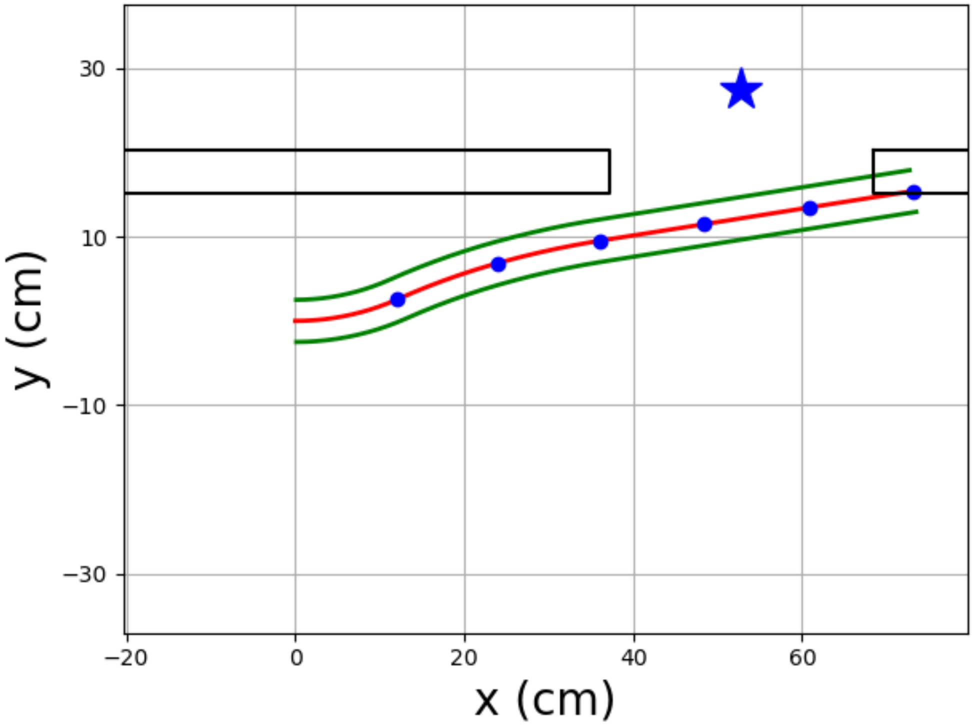




Goal configuration

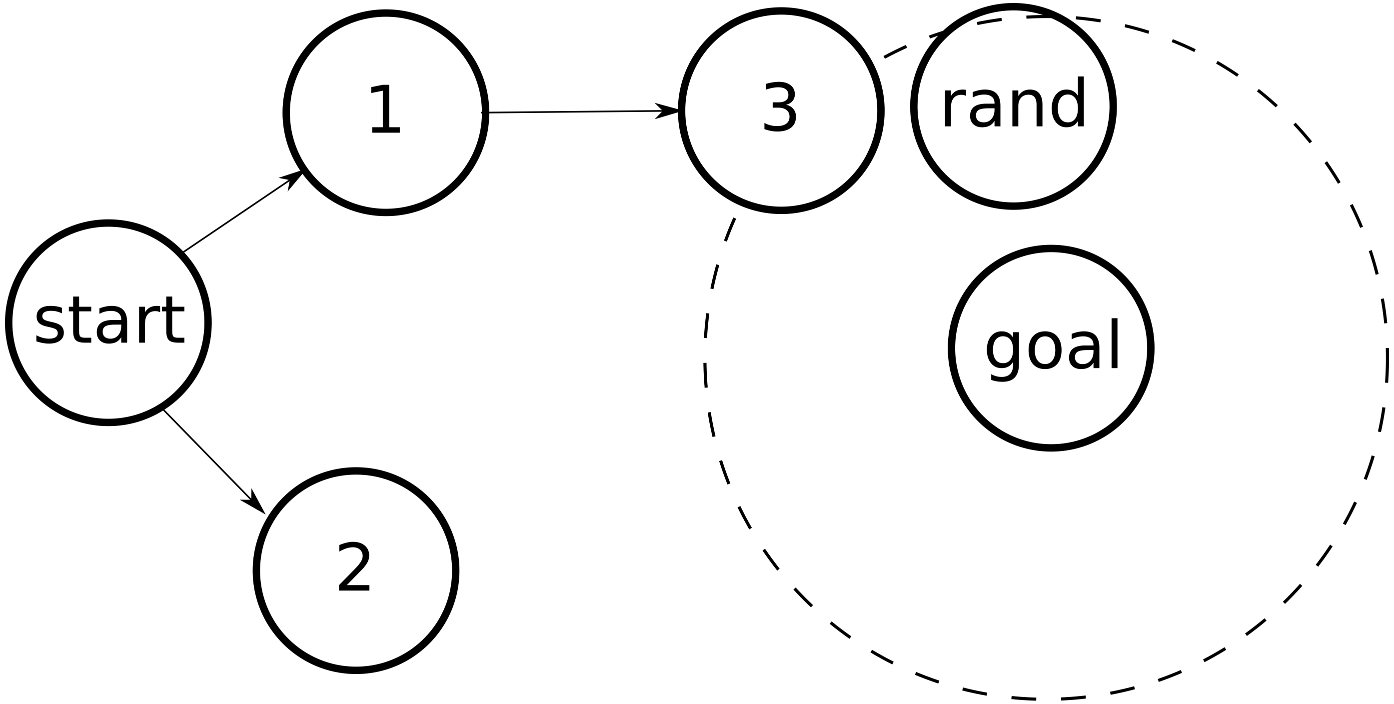
Background: Rapidly-Exploring Random Trees

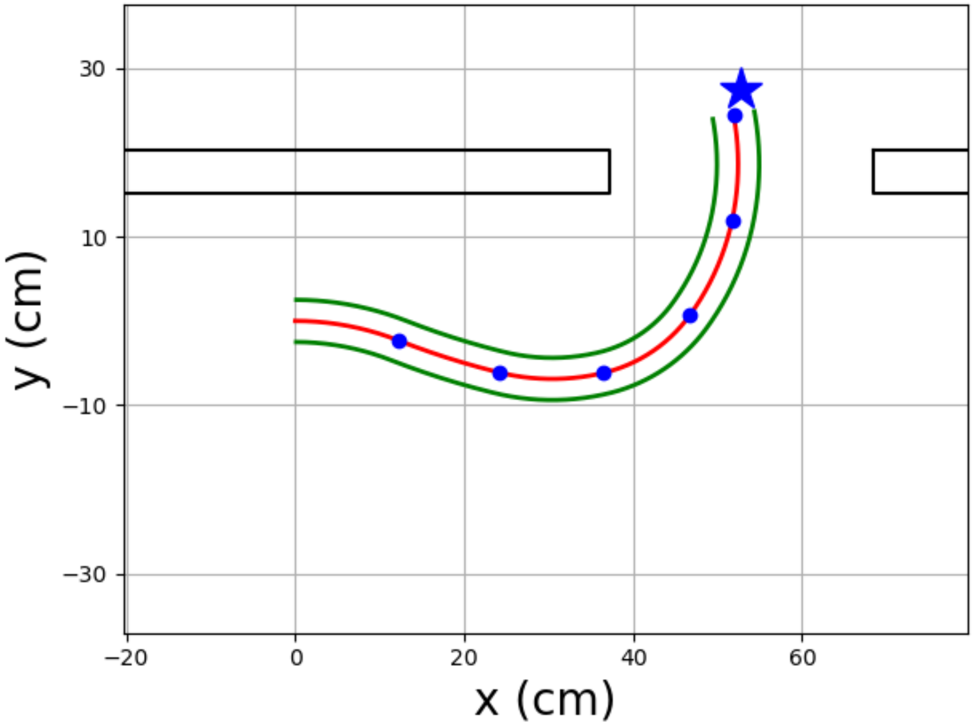




Node 3

Background: Rapidly-Exploring Random Trees





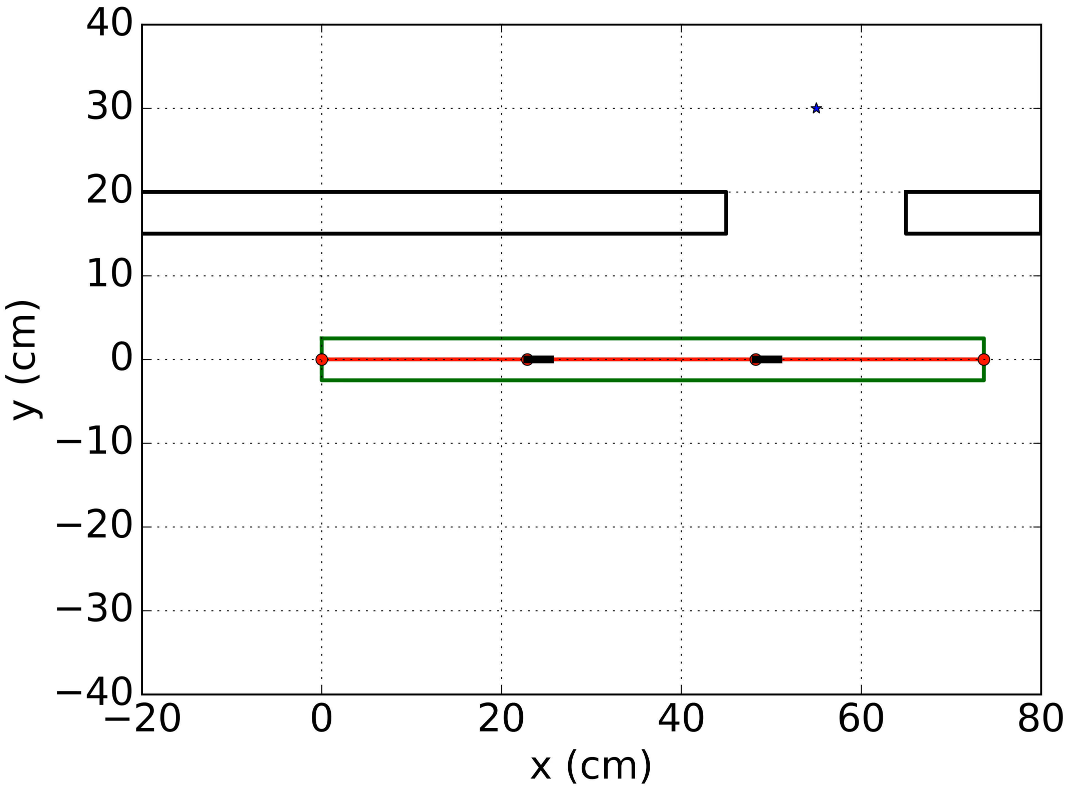
Node 3

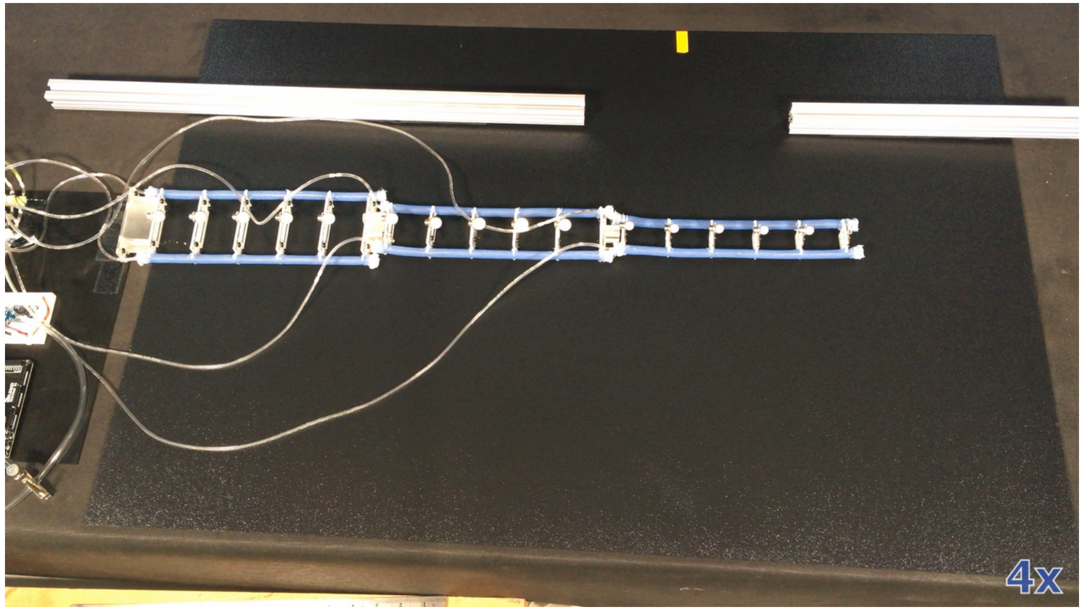
Simulation Results

Arm Thickness (cm)	5.0	4.0	3.0	1.8
Max Curvature (cm^{-1})	0.044	0.055	0.073	0.122
Successful Plans	40	39	41	39
% out of Feasible	95.2%	92.9%	97.6%	92.9%

- > 90% success rate out of feasible plans for all thicknesses
- Simple RRT works well enough for 3 segment arm

Hardware Demonstration





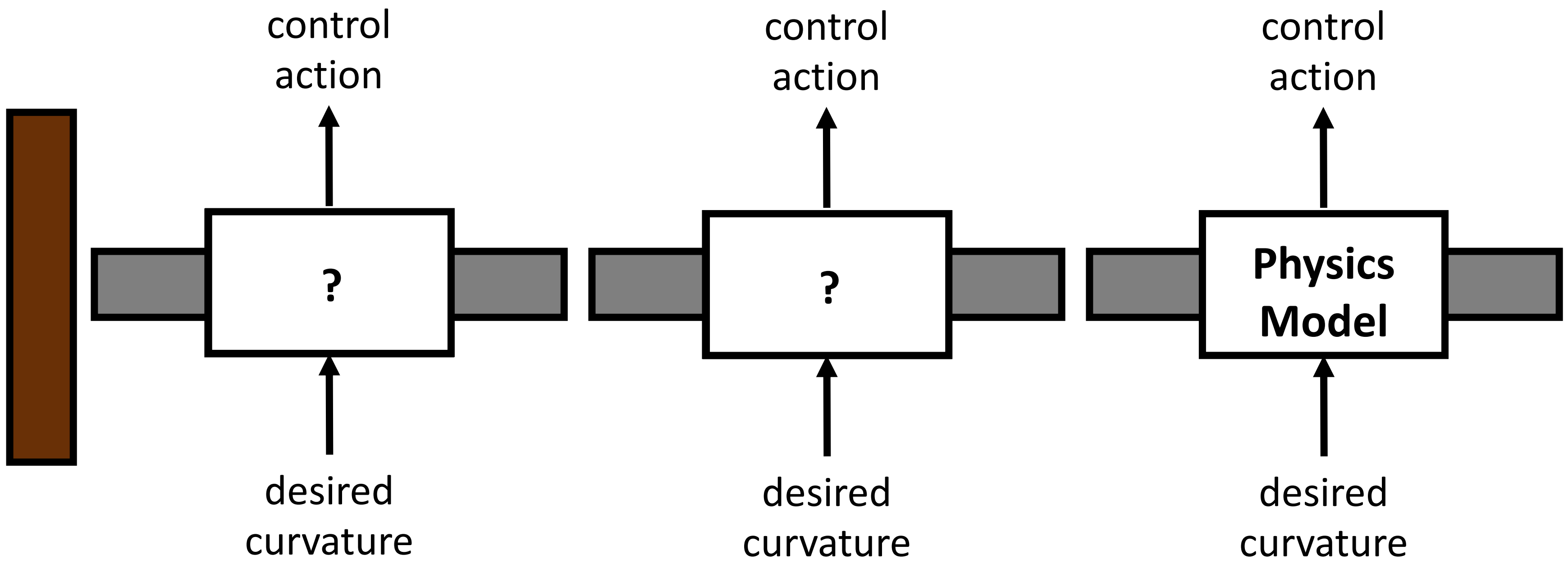
Summary

Using current approaches for soft robot planning:

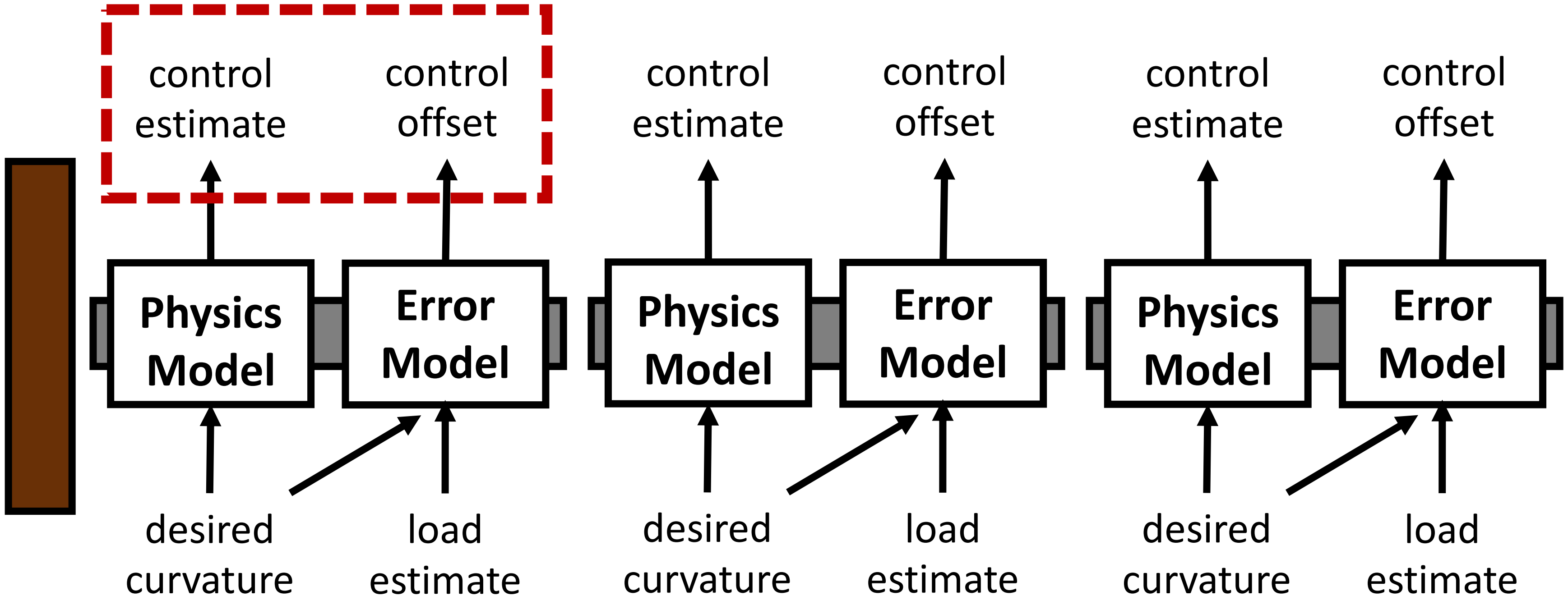
- Utilized our simulator to create motion plans
- RRTs can be adapted to generate plans for soft manipulators
- Demonstrated motion planning on a physical arm

Gina Olson, **Scott Chow**, Austin Nicolai, Callie Branyan, Geoffrey Hollinger, Yiğit Mengüc. "A generalizable equilibrium model for bending soft arms with longitudinal actuators." *International Journal of Robotics Research*, Oct. 2019

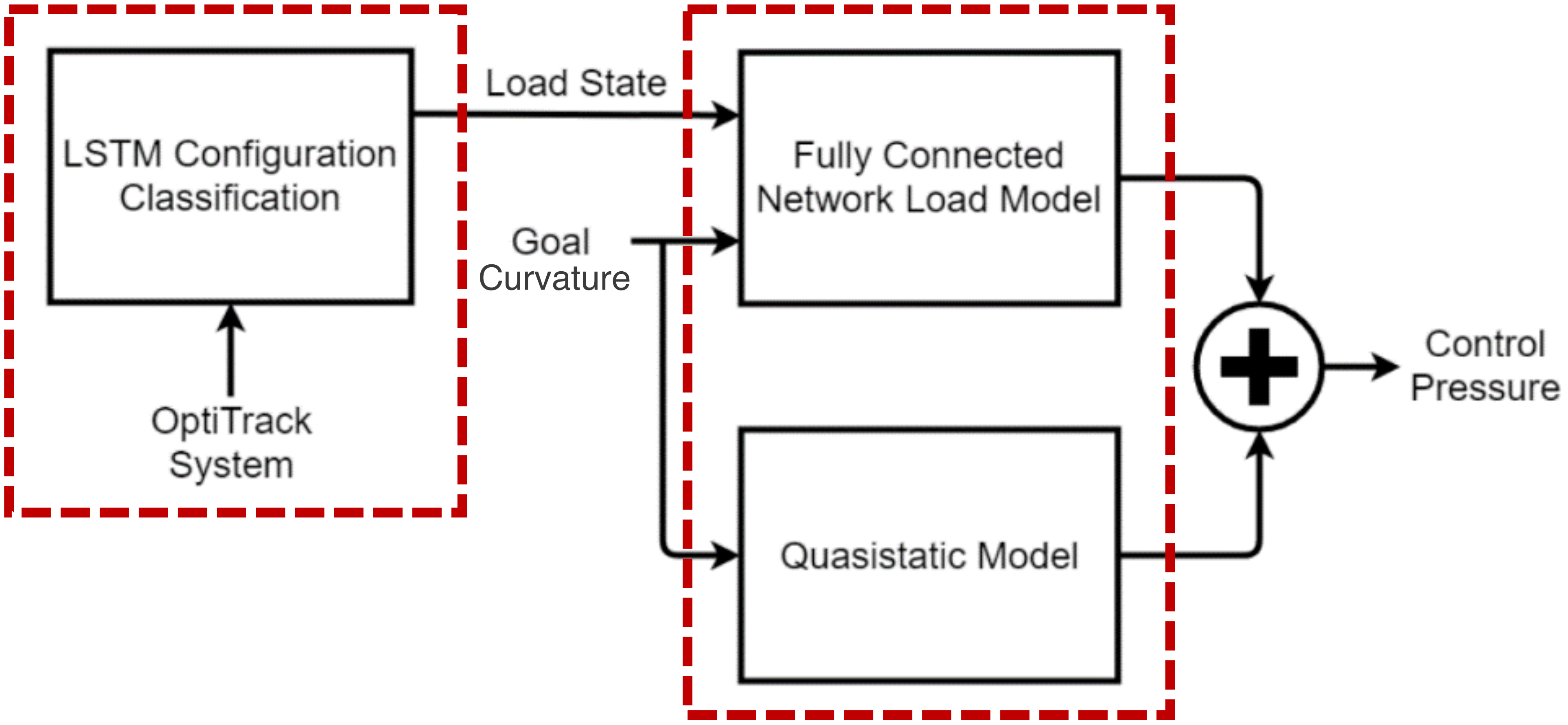
Model-Based Control



Hybrid Control

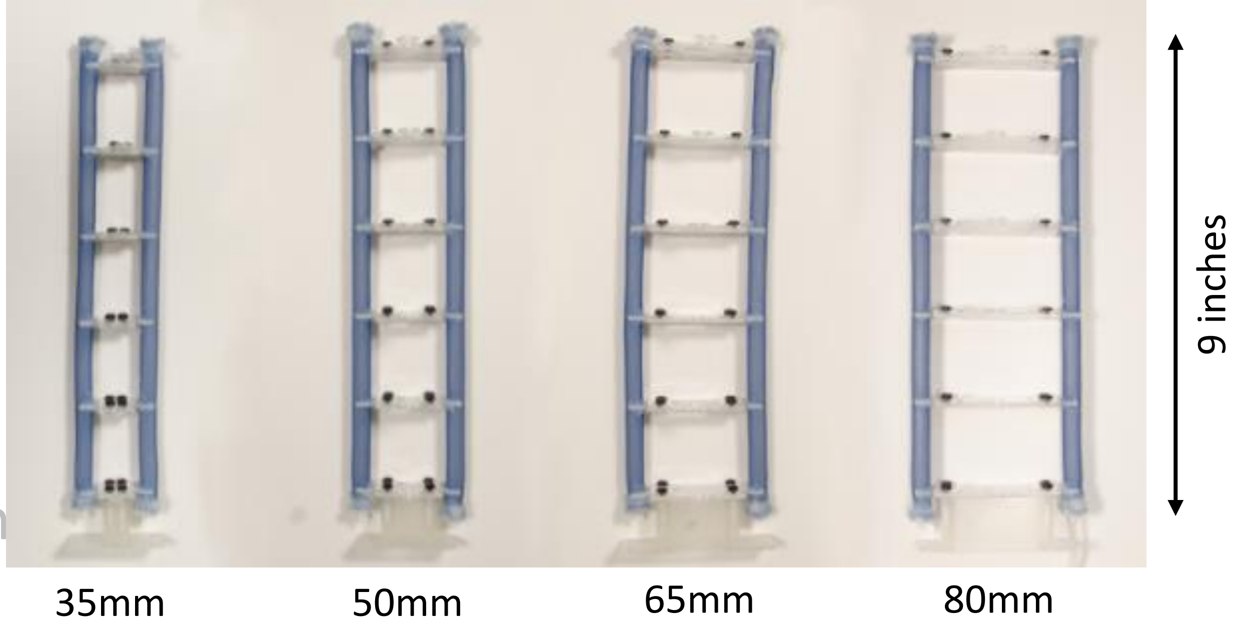


Proposed Approach



Load State Estimation: Method

- Staged arm configurations
  - Consecutive links widths decrease
- 4 widths
  - 80mm used as base link
  - 65mm, 50mm, 35mm vary position
- 3 arm configurations
  - 80-65-50
  - 80-65-35
  - 80-50-35



unique load states

Load State Estimation: Method

- Pressure vs curvature curves are smooth
  $(u_{base}, \kappa_{base})_i$ highly predictive of $(u_{base}, \kappa_{base})_{i+1}$

- Take advantage of this temporal relationship using an LSTM

- Sweep through entire actuator pressure range and classify configurations using all $(u_{base}, \kappa_{base})$ pairs

Load State Estimation: Training Data

- Not efficient to generate thousands of sweeps by hand
- Augment training data by stitching together portions of recorded sweeps
- Mimics real-world disturbances

Control Input Mapping: Method

- Decompose control input prediction
  - A
- Benefits:
  - Minimize error from incorrect network predictions
  - Model gives lower bound
  - Actuator ratings give upper bound
- Learn using fully connected deep network
  - Inputs: (s, κ)
  - Output: u_{load}

Control Input Mapping: Training Data

- Efficiently gather from entire arm sweeps
  - Many input/output pairs per sweep
  - Each sweep performs slightly different so data pairs are naturally varied

- Combine all data into single distribution
  - $(\mathbf{u}, \boldsymbol{\kappa}, \mathbf{s}) = P_{load_t} + N(\mu, \sigma^2)$

Experiment 1: Classification Accuracy

- Methods:
  - Fully Connected (baseline)
  - **LSTM (ours)**

- Metrics:
  - Precision
  - Recall

	Precision				Recall			
	Mean	80-65-50	80-65-35	80-50-35	Mean	80-65-50	80-65-35	80-50-35
Fully Connected	94.85%	100.0%	88.89%	95.65%	94.67%	100.0%	96.0%	88.0%
LSTM (proposed)	97.33%	100.0%	96.0%	96.0%	97.33%	100.0%	96.0%	96.0%

- Network Size:
  - **Fully Connected:** 250,883
  - **LSTM:** 11,373
- Convergence Time:
  - **Fully Connected:** 326 epochs
  - **LSTM:** 287 epochs

- LSTM is more accurate
- LSTM is more efficient

Experiment 2: Curvature Accuracy

Fewer Load States →

	80mm Segment		65mm Segment		50mm Segment	
	Mean Error (m^{-1})	Max Error (m^{-1})	Mean Error (m^{-1})	Max Error (m^{-1})	Mean Error (m^{-1})	Max Error (m^{-1})
Curvature Control (baseline)	0.015 ± 0.011	0.047	0.022 ± 0.016	0.062	0.026 ± 0.017	0.079
Individual Curve Fit Control	$\mathbf{0.037 \pm 0.021}$	**0.086**	0.189 ± 0.152	0.552	0.076 ± 0.047	0.160
Single Surface Fit Control	0.071 ± 0.041	0.175	0.204 ± 0.177	0.551	0.082 ± 0.052	0.194
Deep Network Control (proposed)	$\mathbf{0.037 \pm 0.028}$	0.123	$\mathbf{0.103 \pm 0.108}$	**0.403**	$\mathbf{0.072 \pm 0.041}$	**0.154**

- Individual fits achieve similar performance as deep network, but scale poorly
- Deep network performs best when link characterization is more challenging (65mm segment)
- Deep network increasingly outperforms the single surface fit as more load states are considered

Experiment 3: End-Effector Accuracy

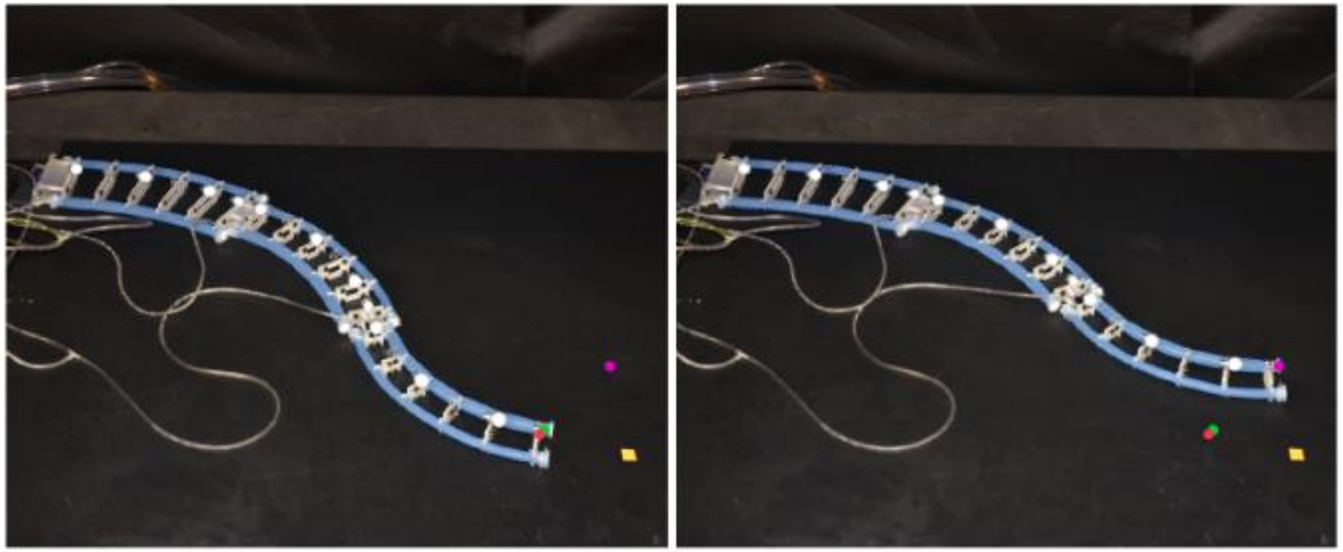
	Arm 80-65-50		Arm 80-65-35		Arm 80-50-35	
	Mean Error (cm)	Max Error (cm)	Mean Error (cm)	Max Error (cm)	Mean Error (cm)	Max Error (cm)
Curvature Control (baseline)	2.791 ± 0.380	3.386	3.342 ± 0.402	4.099	3.672 ± 0.626	5.103
Quasistatic Model Only Control	9.215 ± 5.535	17.267	9.572 ± 5.484	18.171	8.110 ± 4.457	15.162
Quasistatic Plus Load Model Control (proposed)	$\mathbf{3.468 \pm 0.512}$	**4.490**	$\mathbf{3.9282 \pm 0.602}$	**5.339**	$\mathbf{4.125 \pm 0.698}$	**5.479**

- Model only control performs very poorly
- Our hybrid approach gets within 1 cm of baseline
- Error in both our approach and baseline due to link shortening along the segment arc

Experiment 3: End-Effector Accuracy

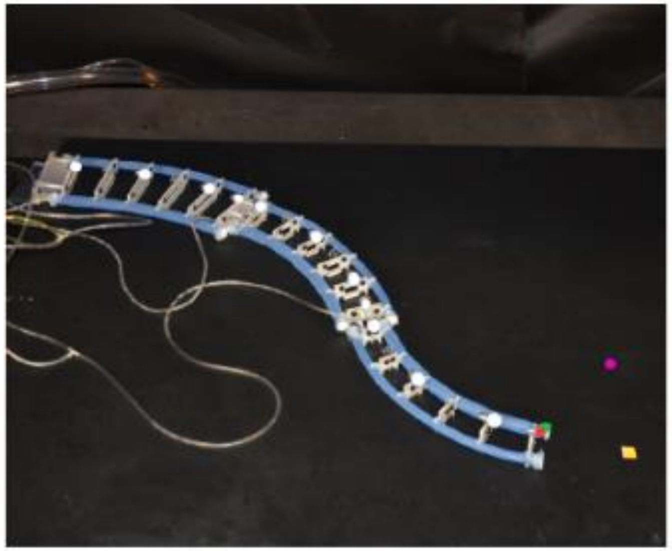
The three dots represent the final end-effector location for the different control methods.

- **Green:** Curvature control
- **Magenta:** Quasistatic model only
- **Red:** Quasistatic plus load model control (proposed)



(a) Curvature control

(b) Quasistatic model only control



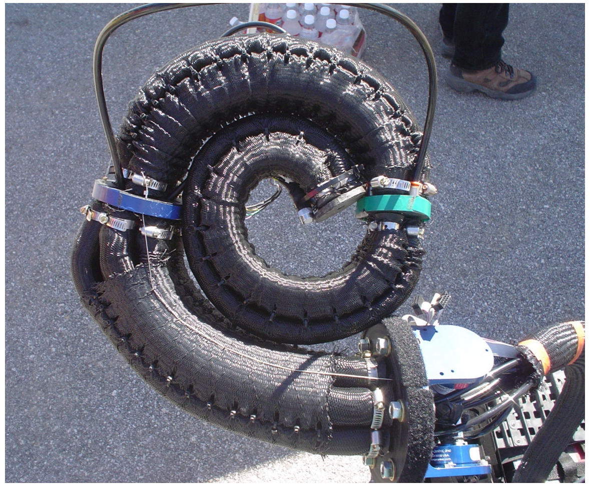
(c) Quasistatic plus load model control

State of affairs

Soft arms exist.

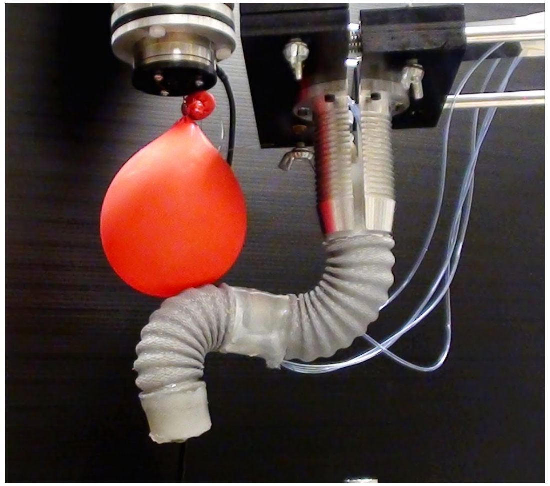
Each arm is capable in at least one aspect.

Large workspace.
Lifted 620 g.



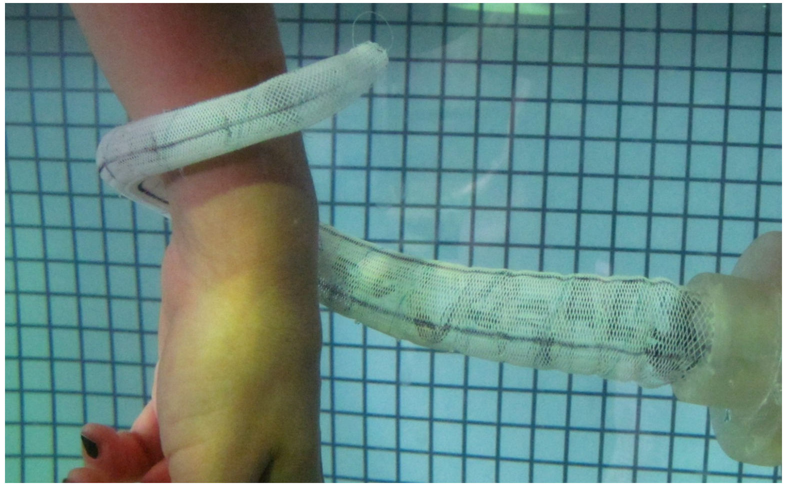
McMahan et al., 2006

Smaller workspace.
Pushed 800 g.



Althoefer, 2015

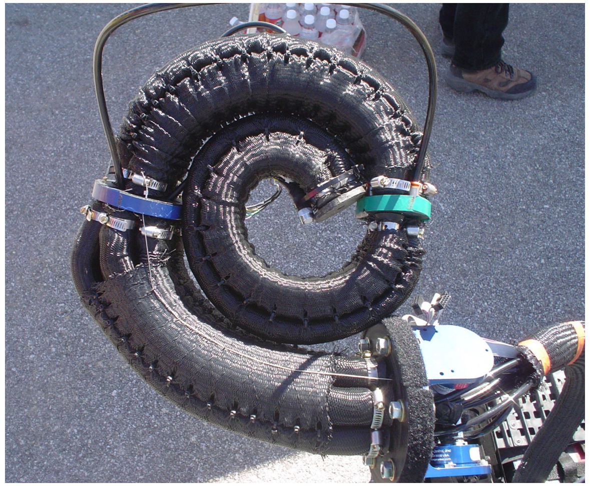
Highly dexterous.
Moves naturally in water.



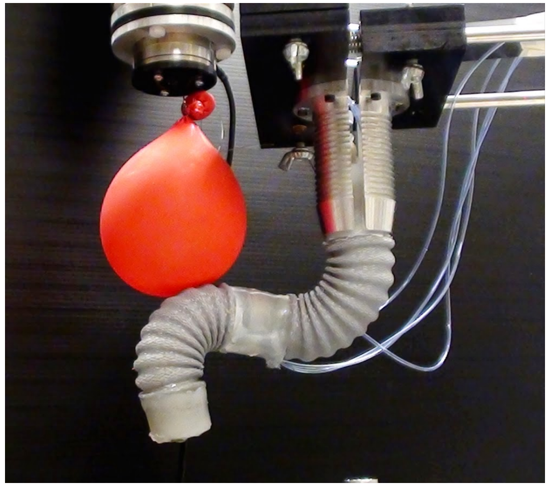
Cianchetti et al., 2012

Problem

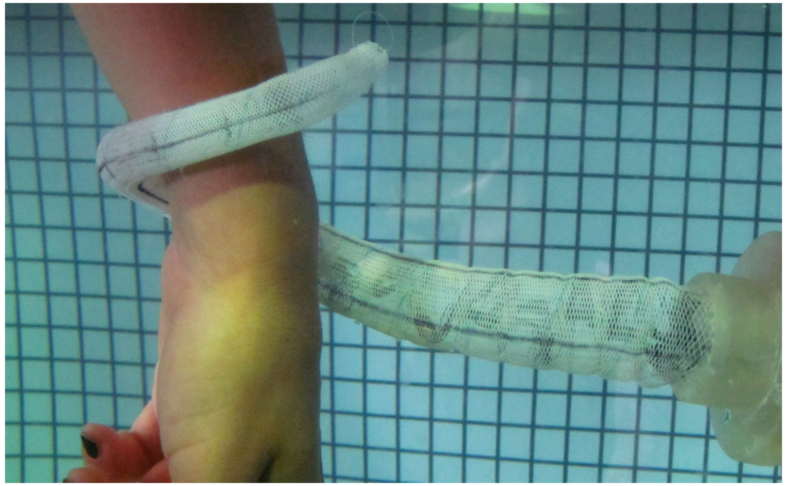
If we wanted a broader workspace or to lift a larger load, would we know how the design should change?



McMahan et al., 2006



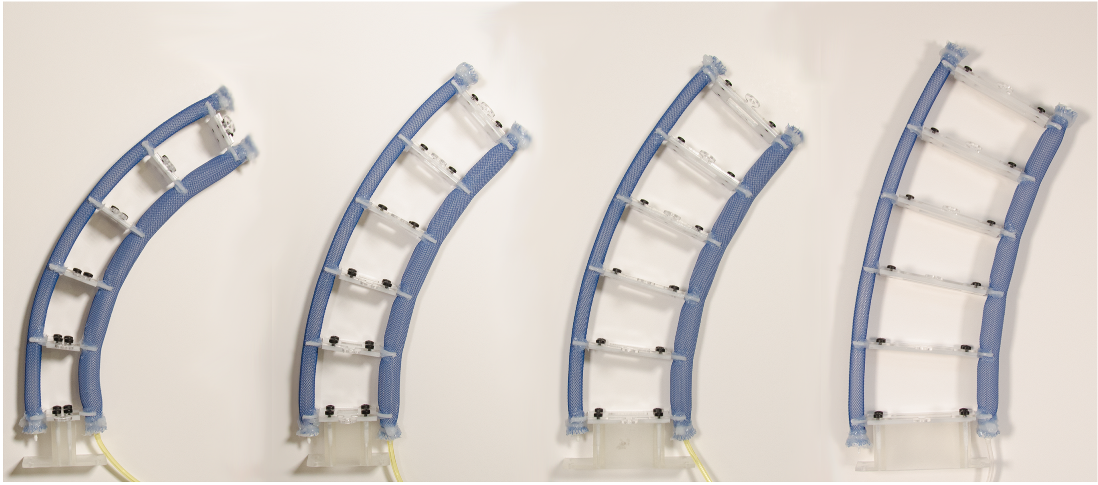
Althoefer, 2015



Cianchetti et al., 2012

Soft arms as designed structures

- Each design has a certain immutable capability (reach & load).
- Model-guided design can identify capable arm architectures…
- …but appropriate generalizable arm models do not exist.



Goal: Develop design analysis tools for soft arms and use them to identify capable soft arm designs.

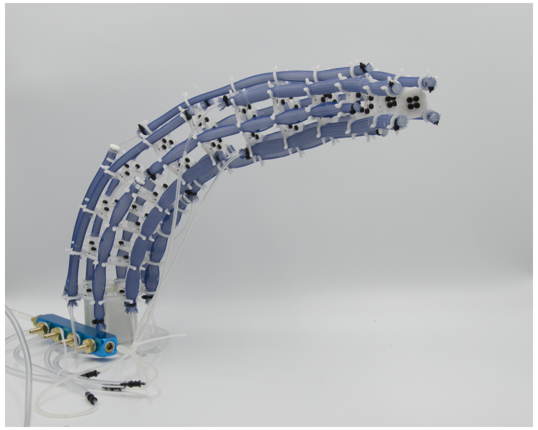
What makes up a soft arm?

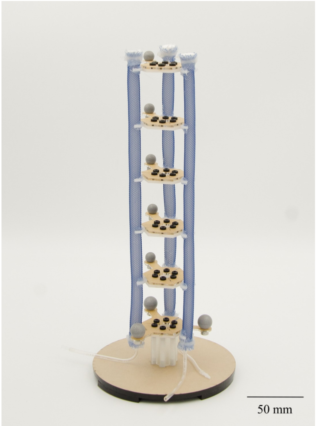
n segments with m_n actuators

Planar

Spatial

(Omnidirectional)





Generalizable models of soft arms

<u>"Top Down" Modeling (not generalizable):</u> Build an arm. Test to determine mass *m,* stiffness *k*, etc. Use parameters in model (e.g., Euler-Lagrange eqs)

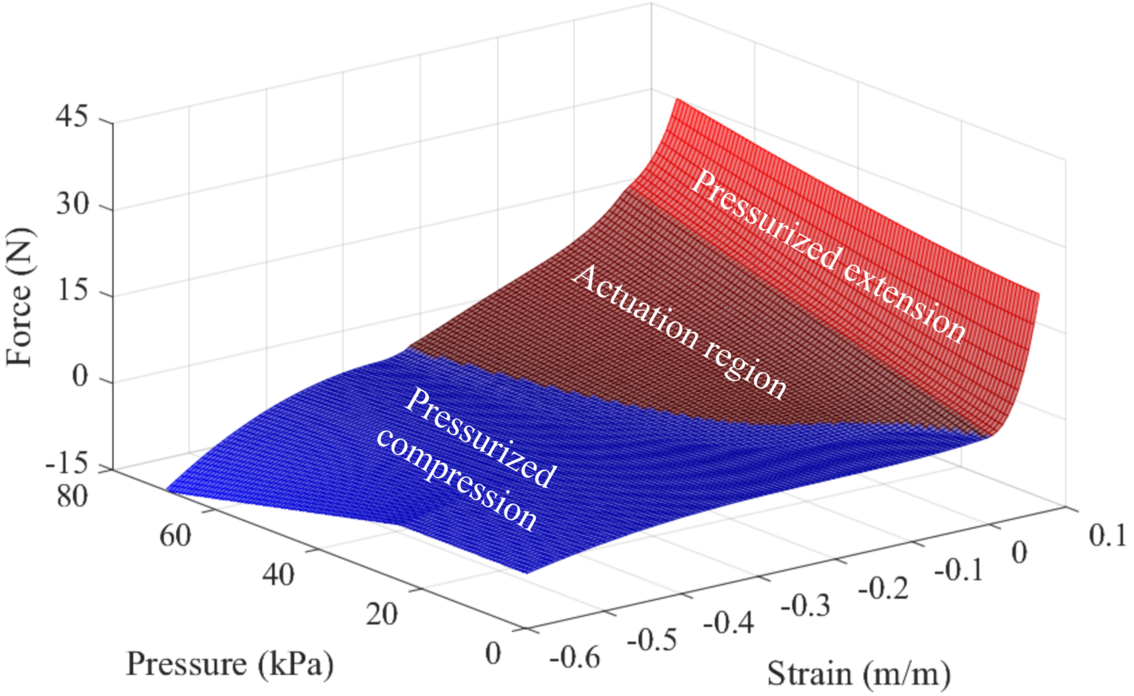
Our approach:

<u>"Bottom Up" Modeling (generalizable):</u> Each actuator produces some force *F* for a given strain and pressure. Arm stiffness is a resultant of combined actuator stiffnesses.

Actuators as active materials

Abstract as *F = F(ε, P)* but models **<u>must</u>** include deformations outside of actuation.

Nominal *Extended*

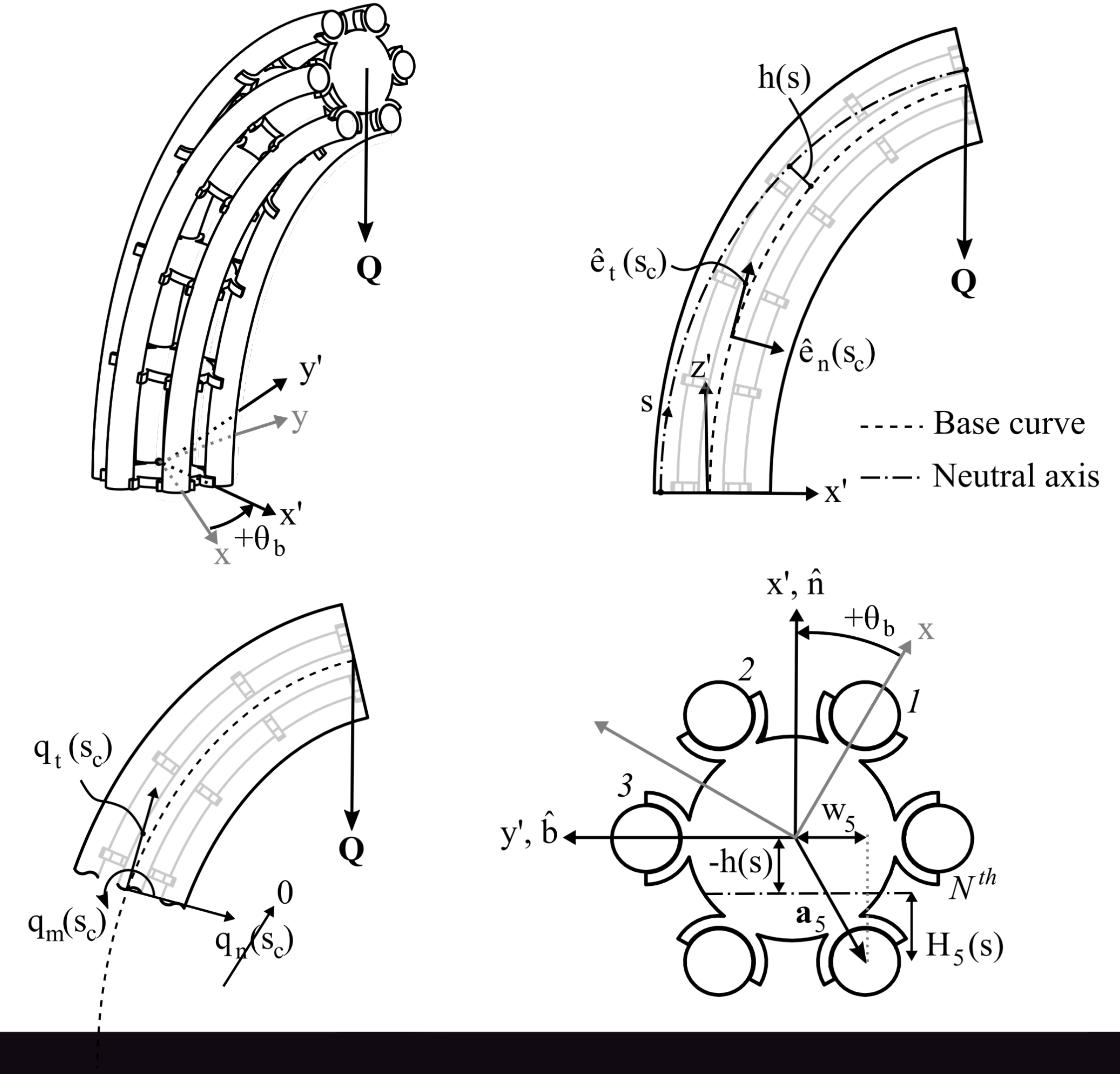


Euler-Bernoulli beam model

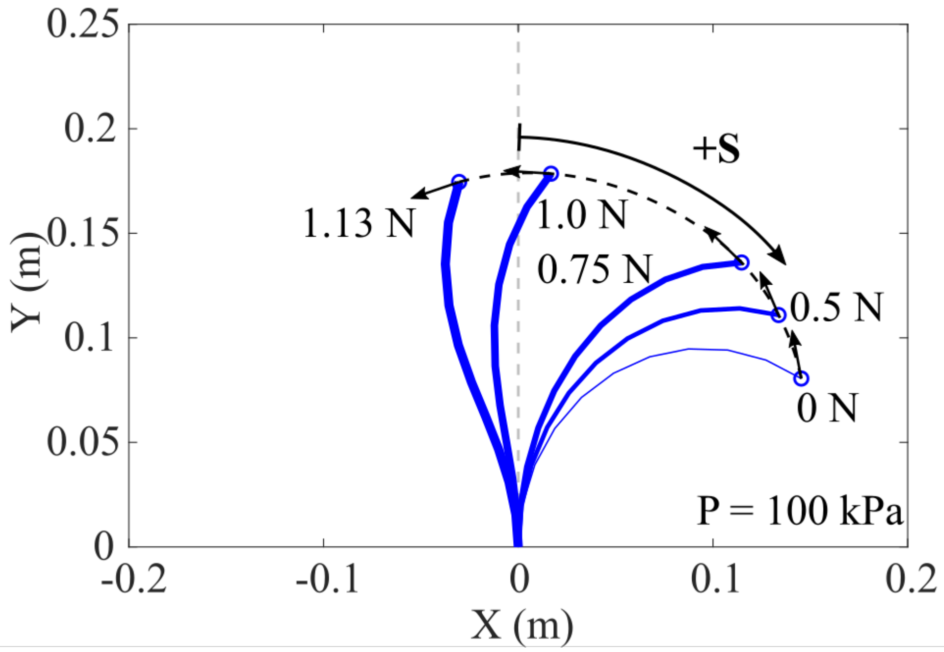
The actuator model is coupled with a Euler-Bernoulli beam model.

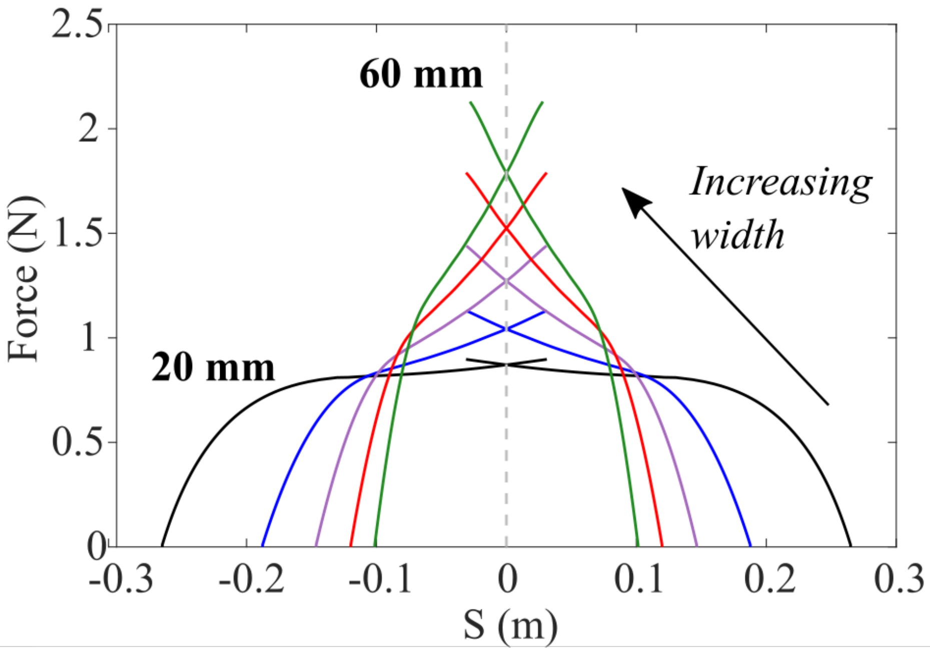
The actuator arrangement and segment lengths are automatically considered.

Model form: discrete, geometrically exact, base curve length change considered.

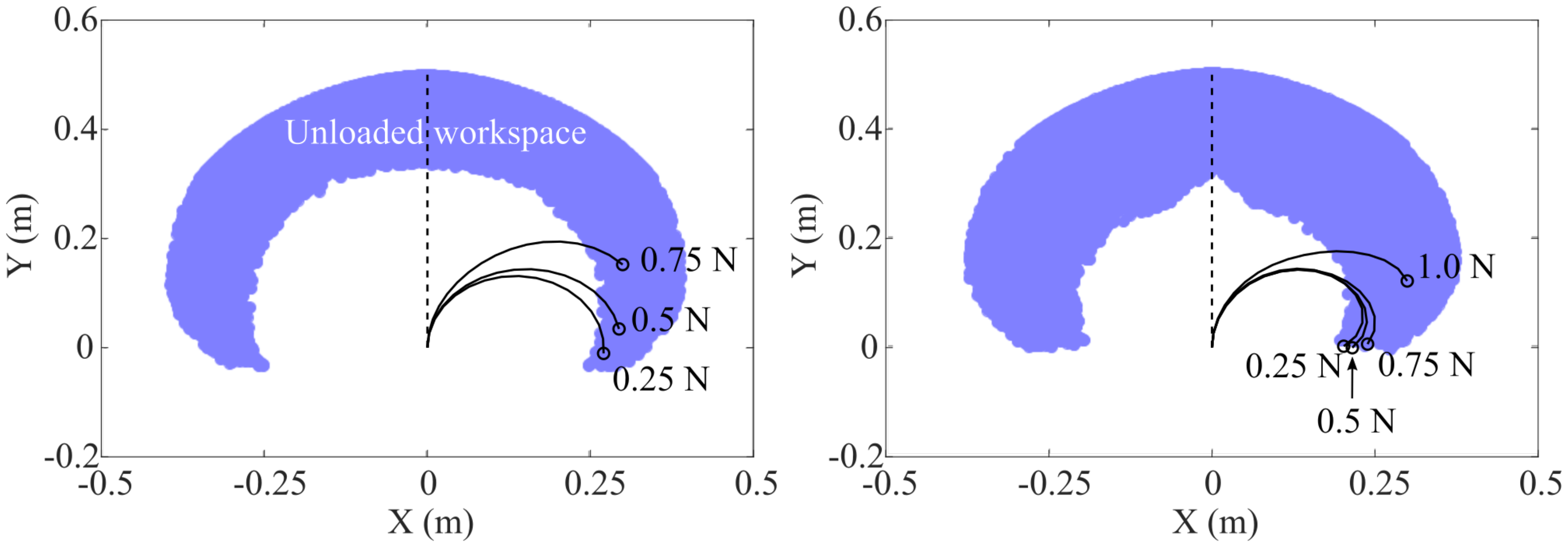


Planar workspace





Taper



Untapered three segment arm **Tapered three segment arm**