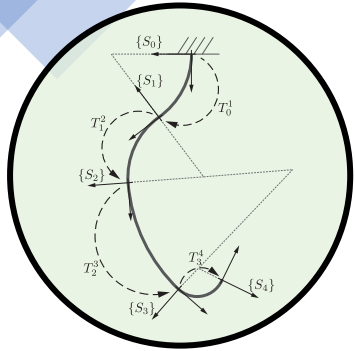


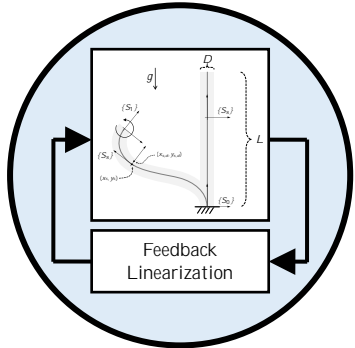


Model your robot for control, and not for simulation!
Insights from a control theoretic perspective

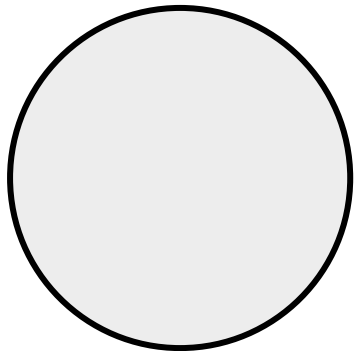
Cosimo Della Santina



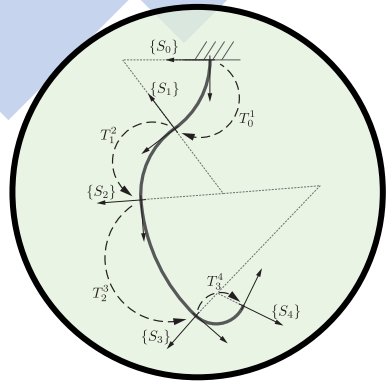
Feedback Model Based Control
Is Robust to Rough Approximations



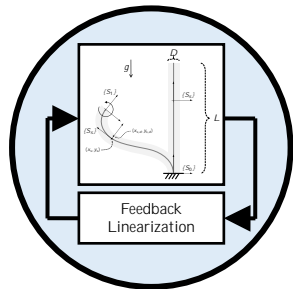
If You Want to Dig More
Do That in a Control Oriented Way



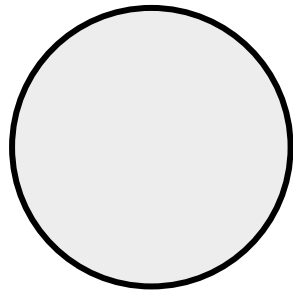
If You Want to Stick to the Simple Model,
Considered Control-Driven Ways to Improve It



Feedback Model Based Control Is Robust to Rough Approximations



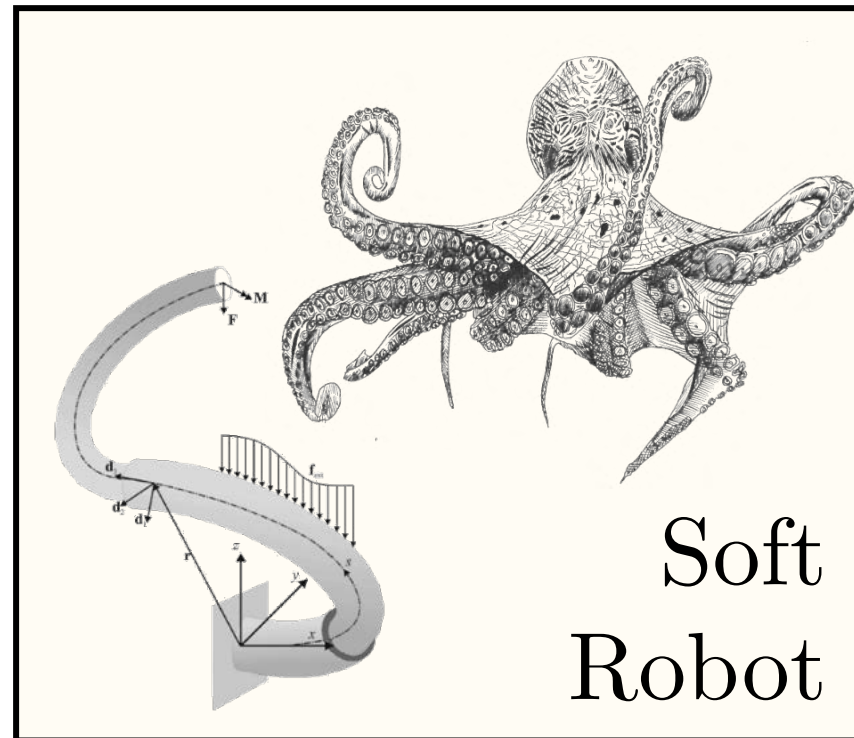
If You Want to Dig More
Do That in a Control Oriented Way



If You Want to Stick to the Simple Model,
Consider Control-Driven Ways to Improve It

A Grand Challenge Within Soft Robotics

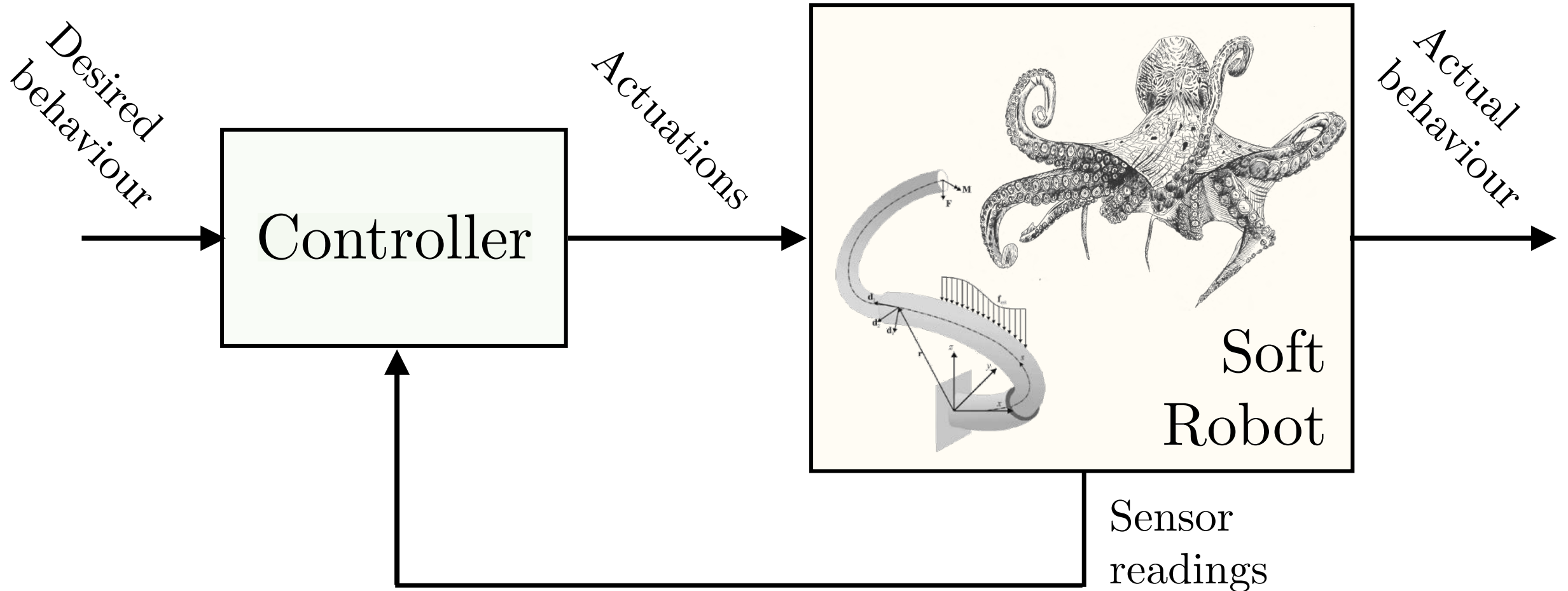
Desired
behaviour



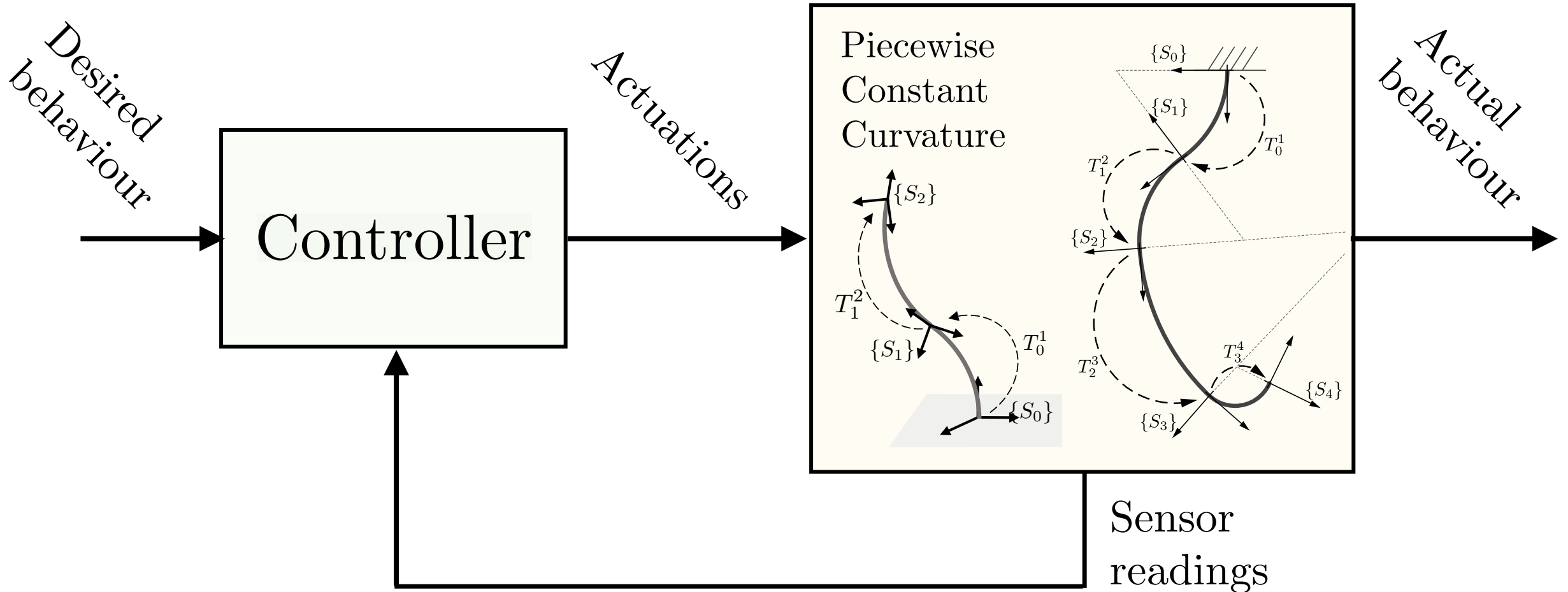
Actual
behaviour



A Grand Challenge Within Soft Robotics

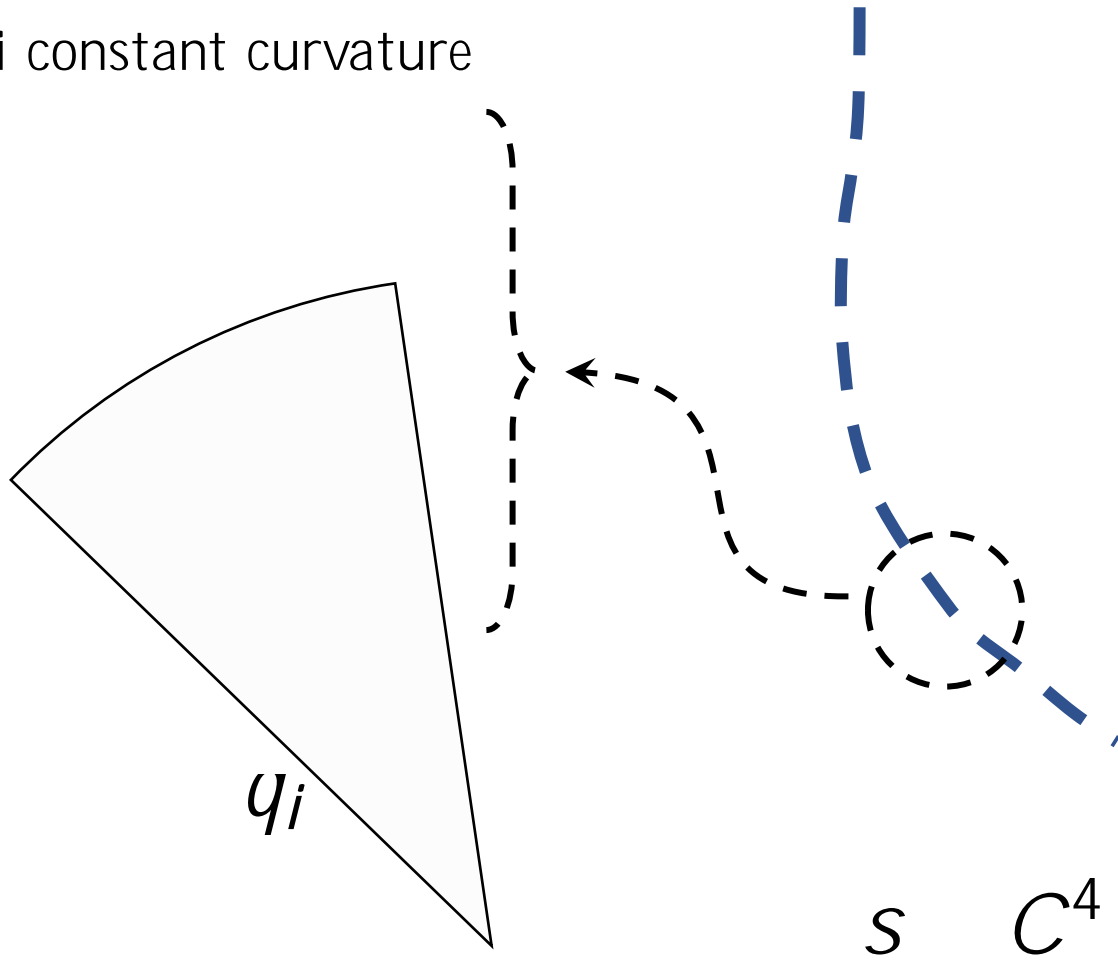


A Grand Challenge Within Soft Robotics



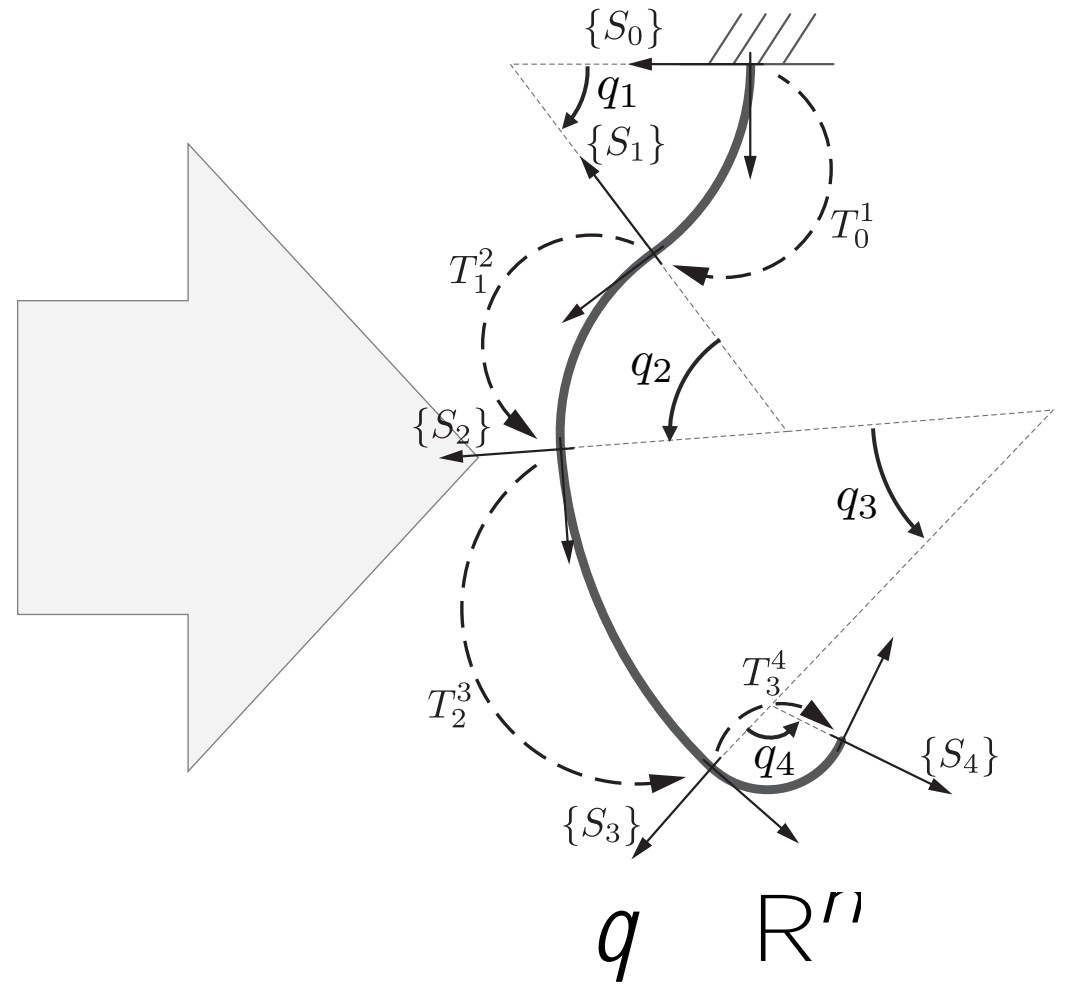
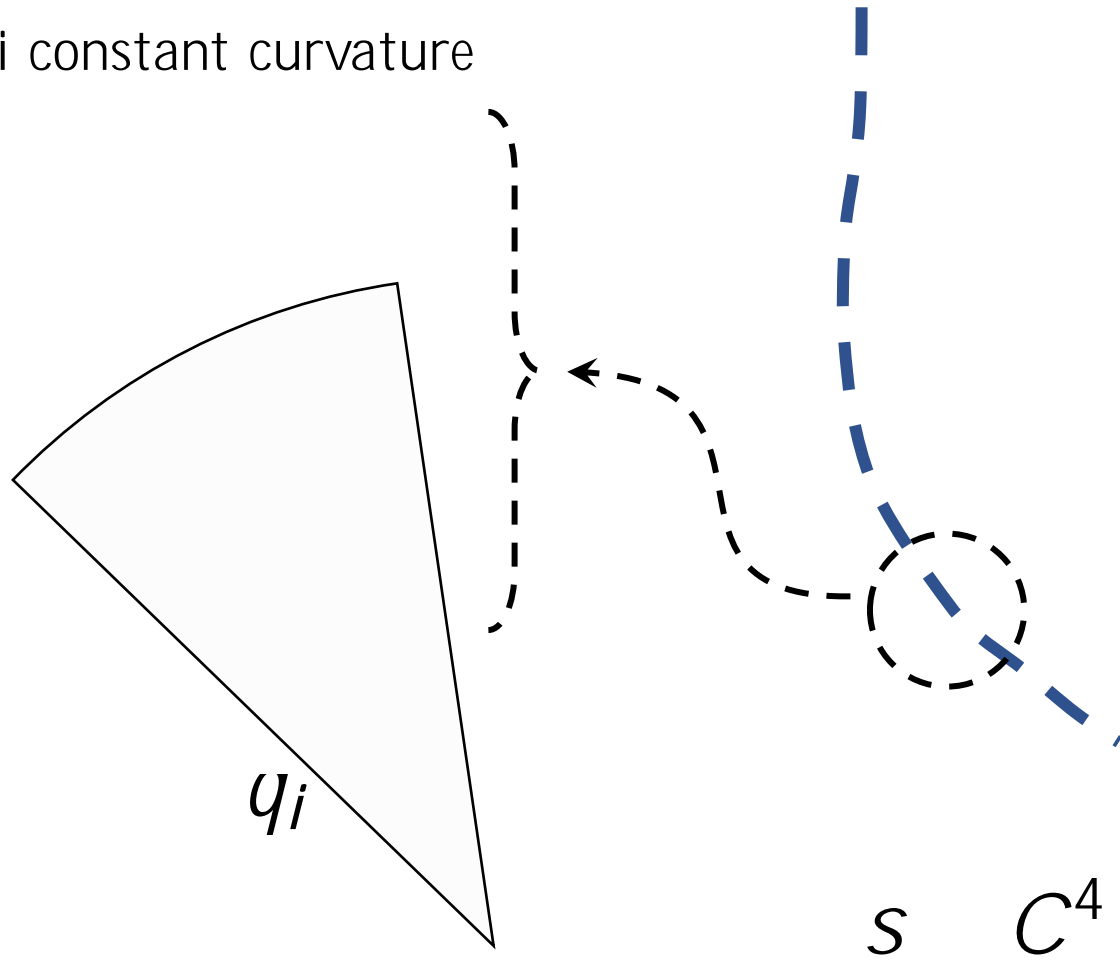
Torques \gg Pure Forces

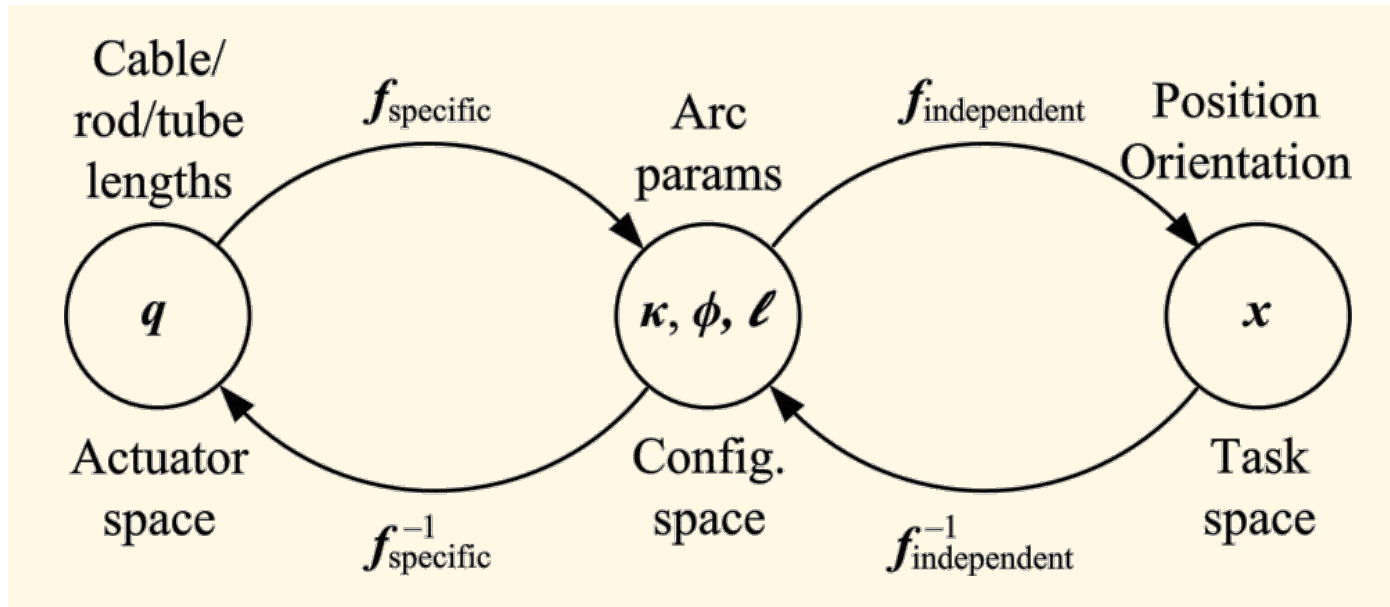
Quasi constant curvature



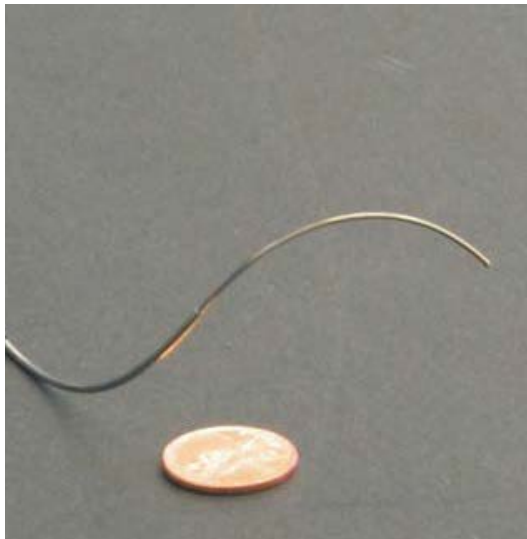
Torques \gg Pure Forces

Quasi constant curvature





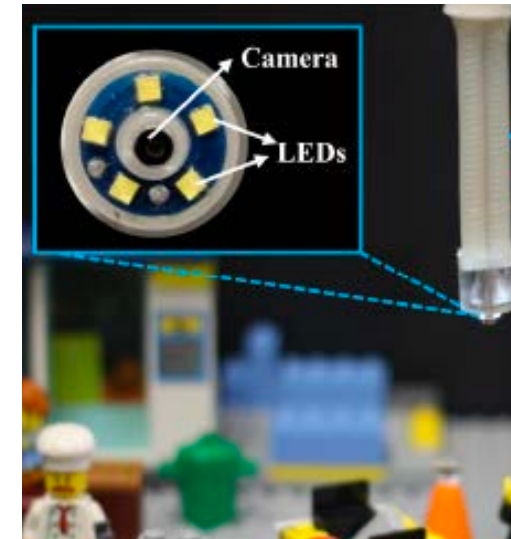
Quasi-static kinematic control



Webster, R. J., III, Romano, J. M. and Cowan, N. J. (2009). Mechanics of precurved-tube continuum robots. *IEEE Transactions on Robotics*



Gravagne, I. A., Rahn, C. and Walker, I. D. (2003). Large deflection dynamics and control for planar continuum robots. *IEEE/ASME Transactions on Mechatronics*, 8(2): 299–307.



Fang, Ge, et al. "Vision-based online learning kinematic control for soft robots using local gaussian process regression." *IEEE Robotics and Automation Letters* 4.2 (2019): 1194-1201.

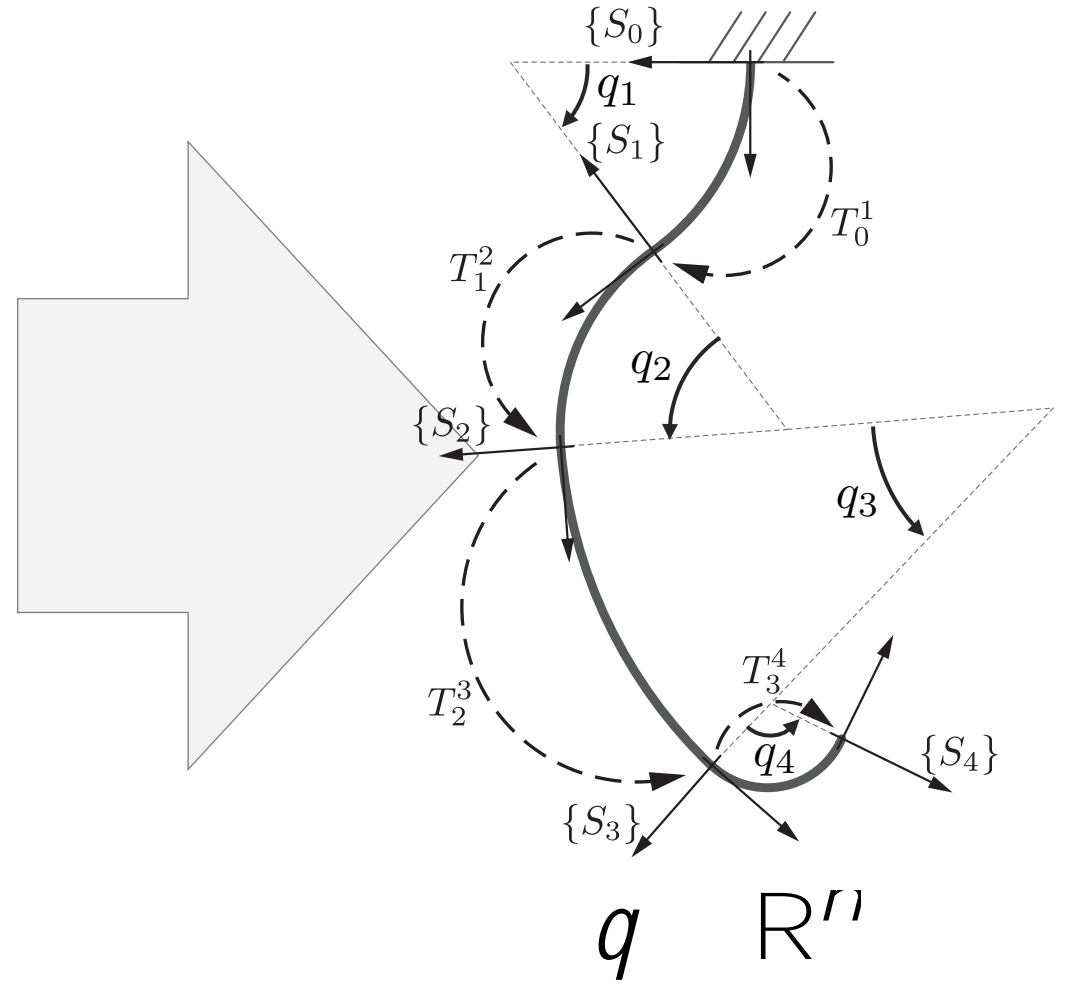
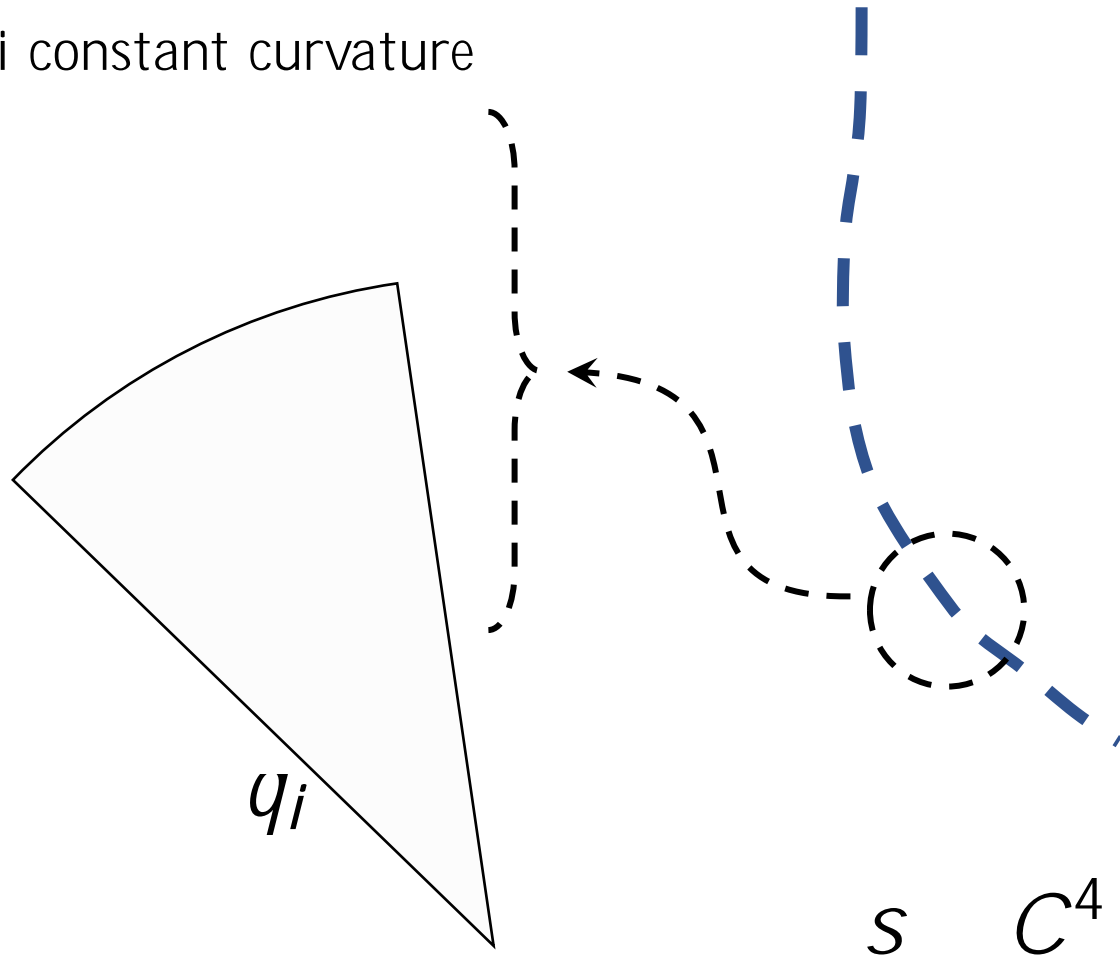
What About Dynamic Control?

(i.e. High speed or high inertias or non negligible interactions or ...)

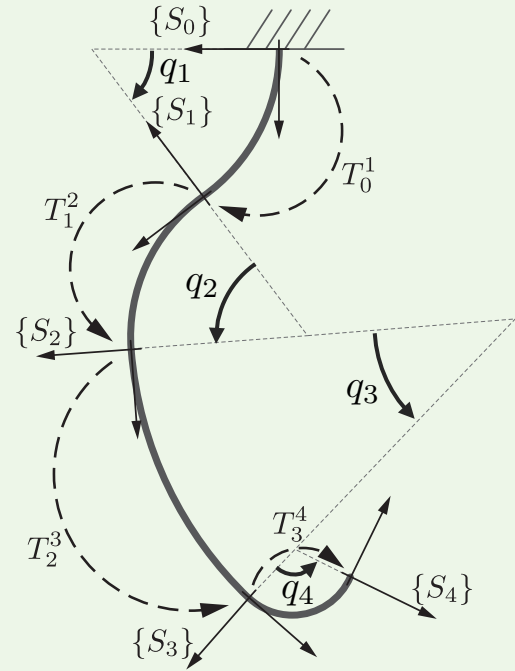


Torques \gg Pure Forces

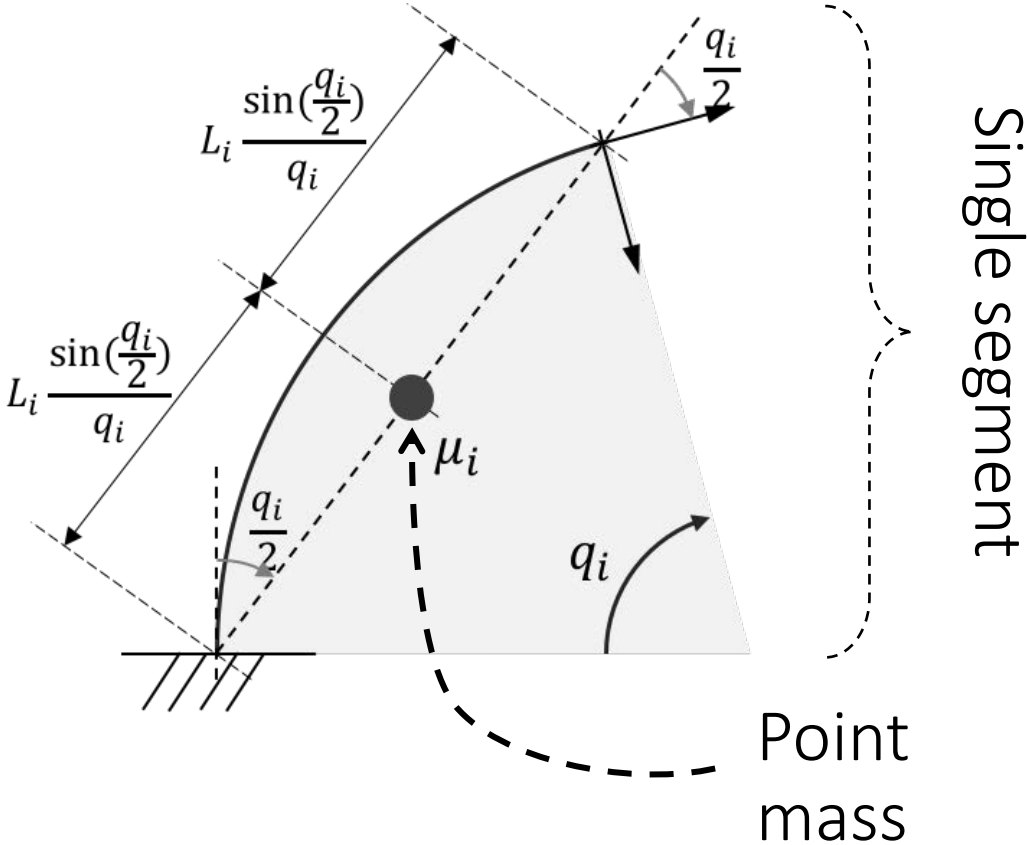
Quasi constant curvature



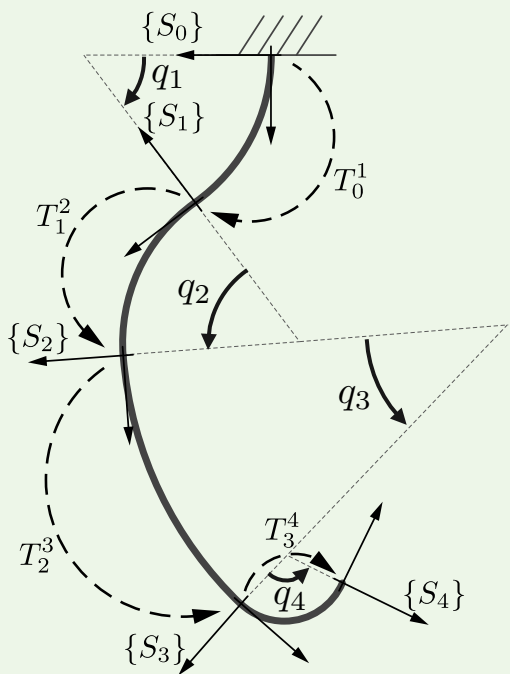
Hypothesis 1 (kinematics):
 SR's can be approximated as a series of n segments with constant curvature (CC)



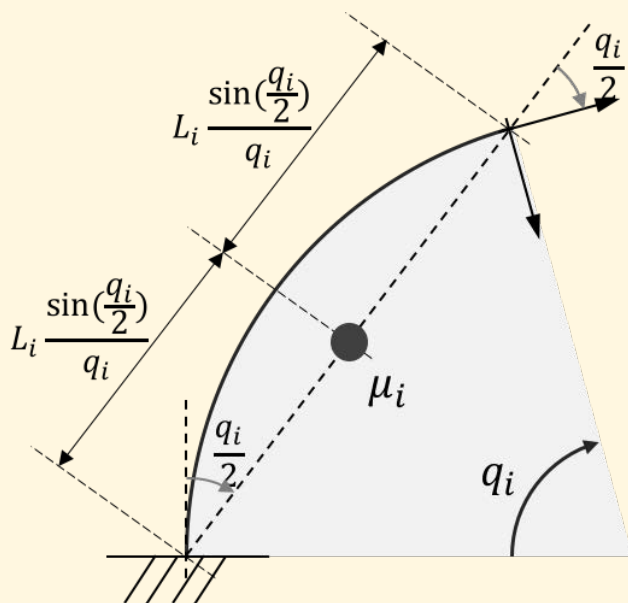
Hypothesis 2 (inertia):
 The inertia of each segment is described by an equivalent point mass.



Hypothesis 1 (kinematics):
SR's can be approximated as a series of n segments with constant curvature (CC)



Hypothesis 2 (inertia):
The inertia of each segment is described by an equivalent point mass.



Hypothesis 3 (impedance):
continuous distribution of infinitesimal springs and dampers

$$L_{\delta,i}(q_i) = (\rho_i - \delta) q_i = \left(\frac{L_i}{q_i} - \delta\right) q_i$$



$$E_{\delta,i}(q_i) = \frac{1}{2} \kappa_i (L_{\delta,i}(0) - L_{\delta,i}(q_i))^2 = \frac{1}{2} \kappa_i \delta^2 q_i^2$$

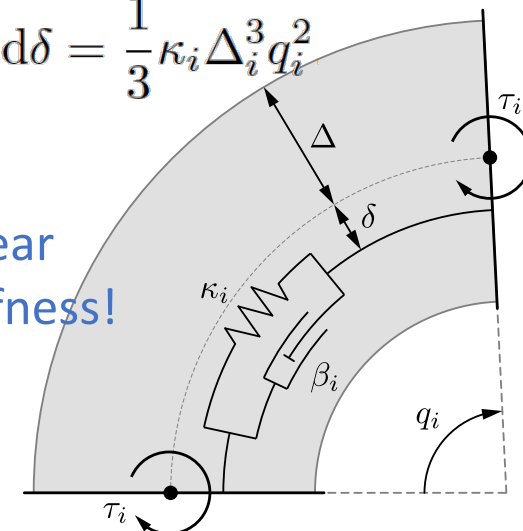


$$E_i(q_i) = \int_{-\Delta_i}^{+\Delta_i} E_{\delta,i}(q_i) d\delta = \frac{1}{3} \kappa_i \Delta_i^3 q_i^2$$



$$\frac{\partial E_i(q_i)}{\partial q_i} = \frac{2}{3} \kappa_i \Delta_i^3 q_i$$

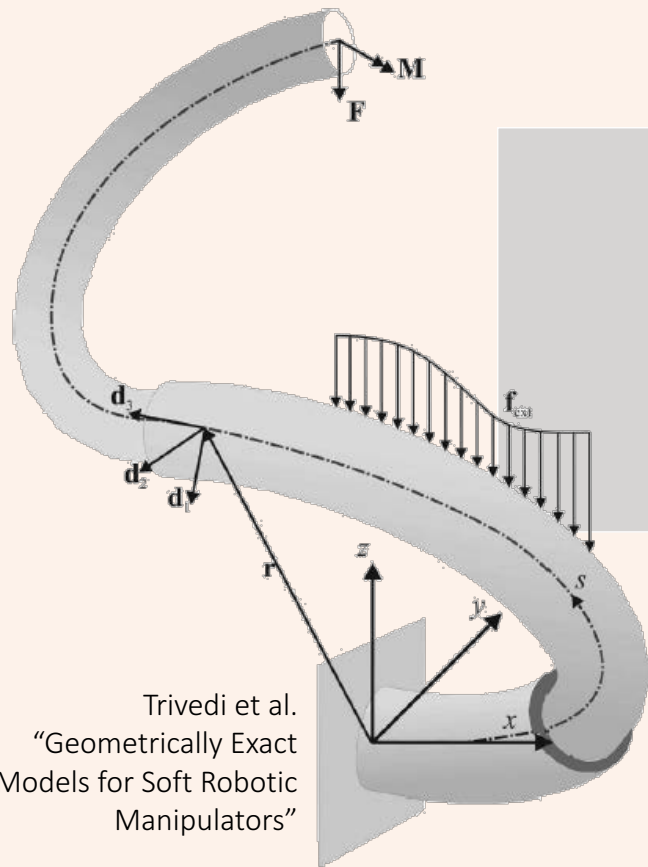
Linear stiffness!



Continuum world

$$(\mathbf{n} - F_{\text{ex}} \mathbf{d}_3)_{,s} + \mathbf{f} = \rho A_t \mathbf{r}_{,tt}$$

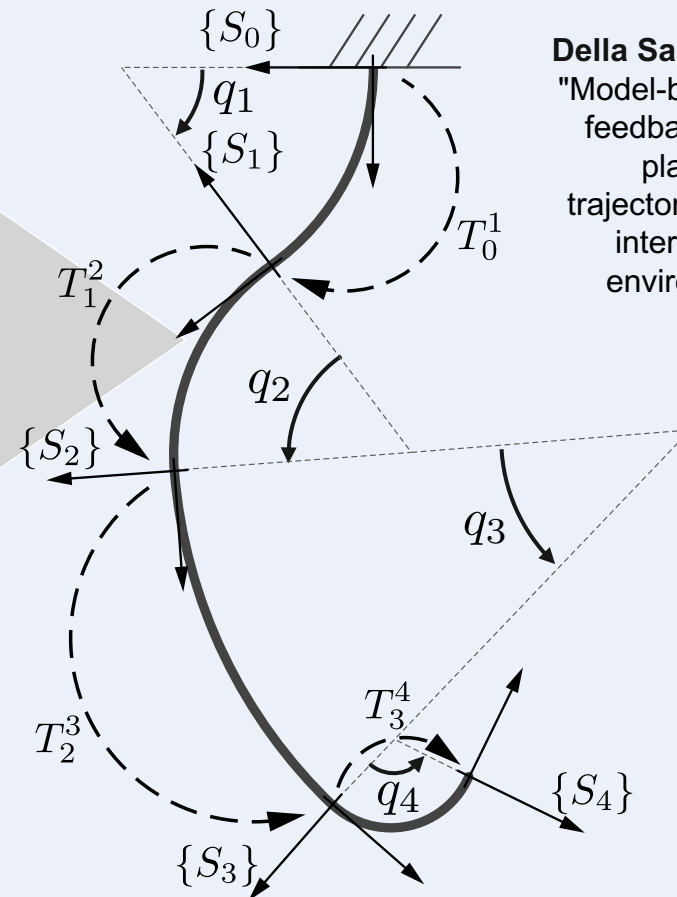
$$\mathbf{m}_{,s} + \mathbf{r}_{,s} \times \mathbf{n} = \mathbf{J} \omega_{,t}$$



Trivedi et al.
"Geometrically Exact
Models for Soft Robotic
Manipulators"

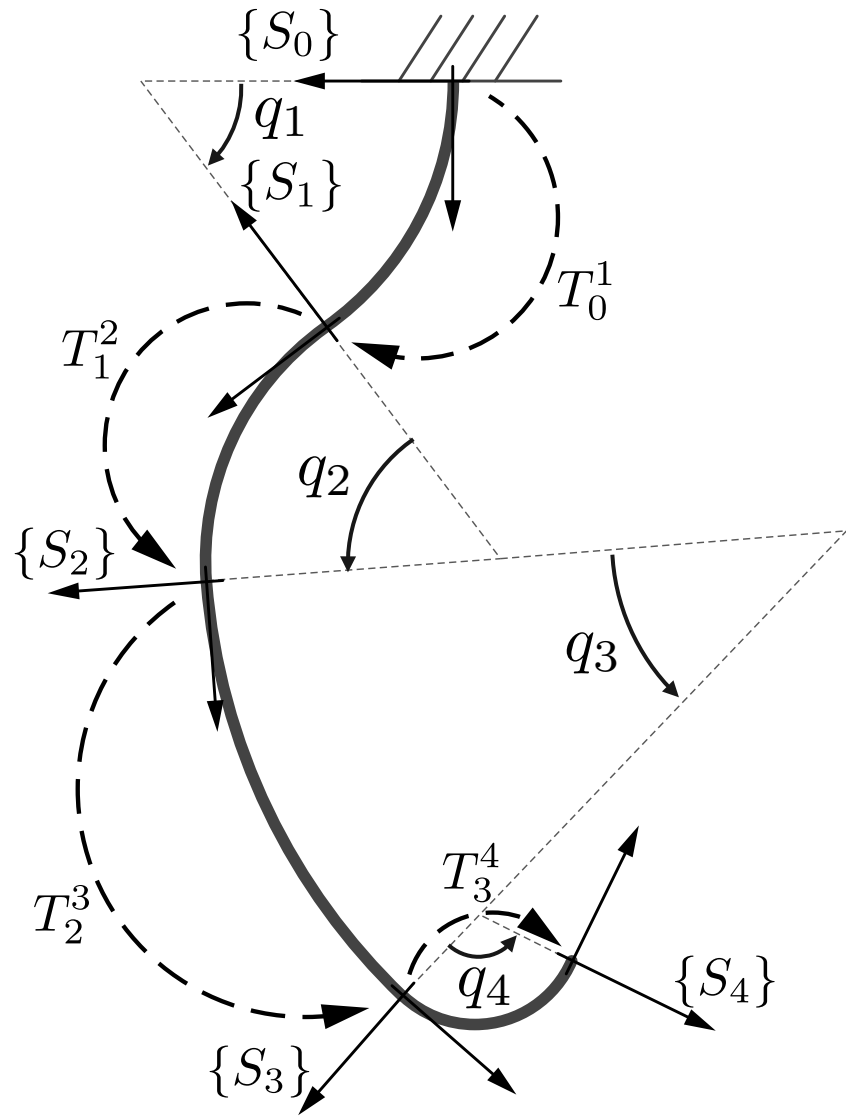
Discrete world

$$B(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) + Kq + D\dot{q} = \tau$$



Della Santina C., et al.
"Model-based dynamic
feedback control of a
planar soft robot:
trajectory tracking and
interaction with the
environment." IJRR

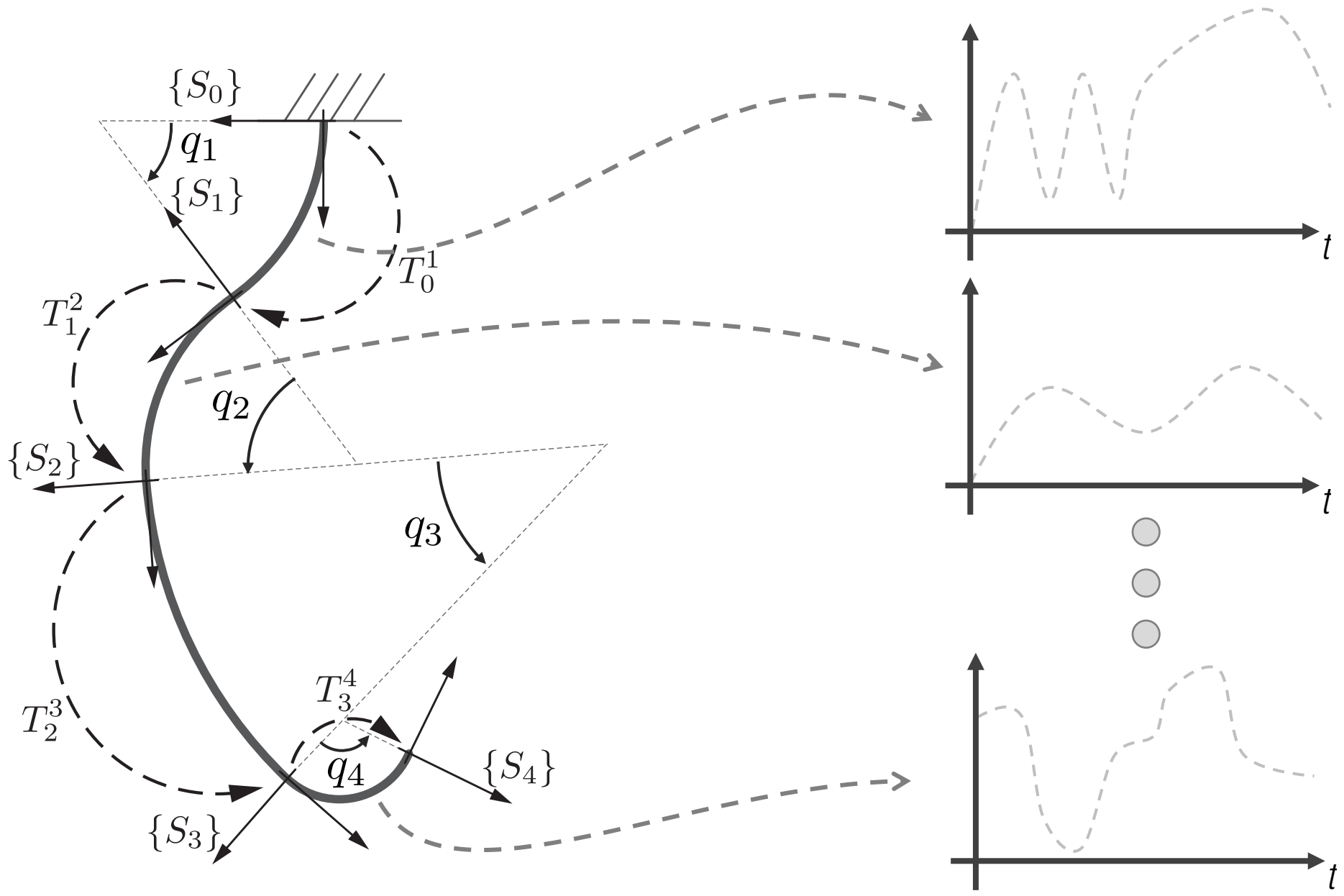




Della Santina C., et al.
 "Model-based dynamic
 feedback control of a
 planar soft robot:
 trajectory tracking and
 interaction with the
 environment." IJRR

Trajectory tracking in **curvature space**

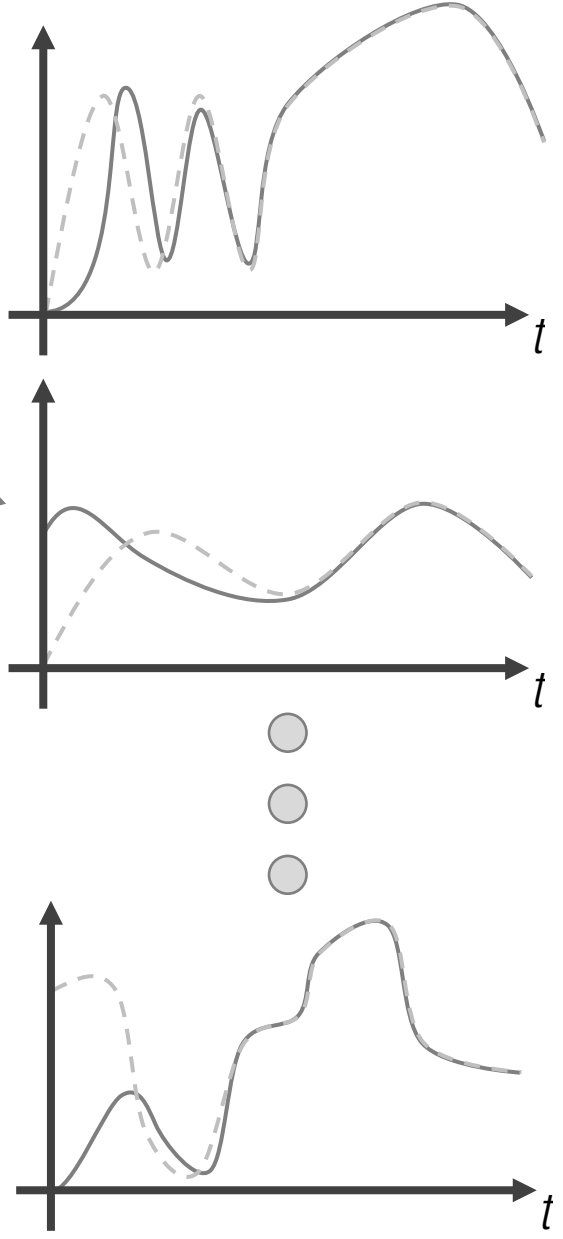
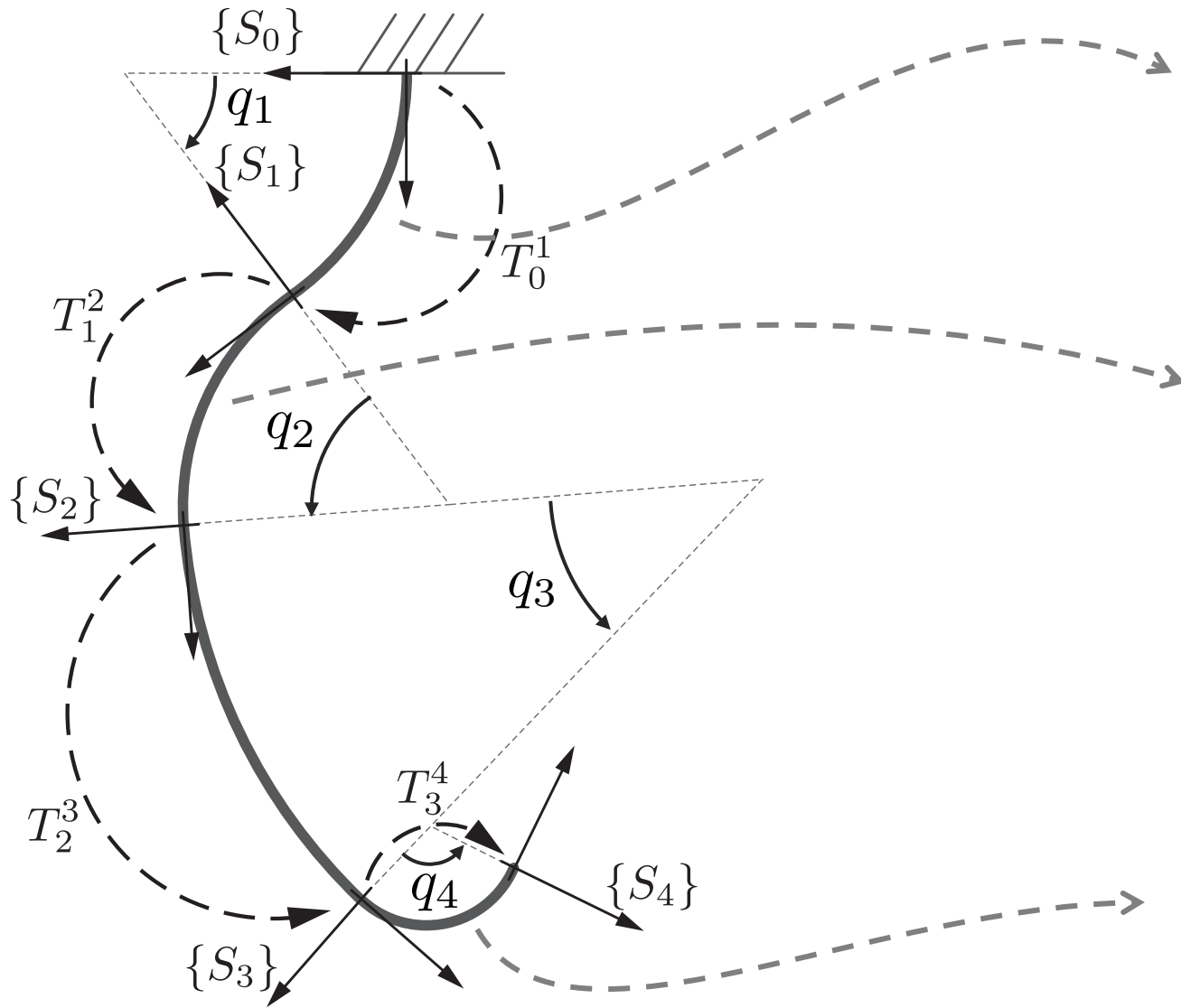
$$\dot{q} = 0$$
$$\ddot{q} = 0$$



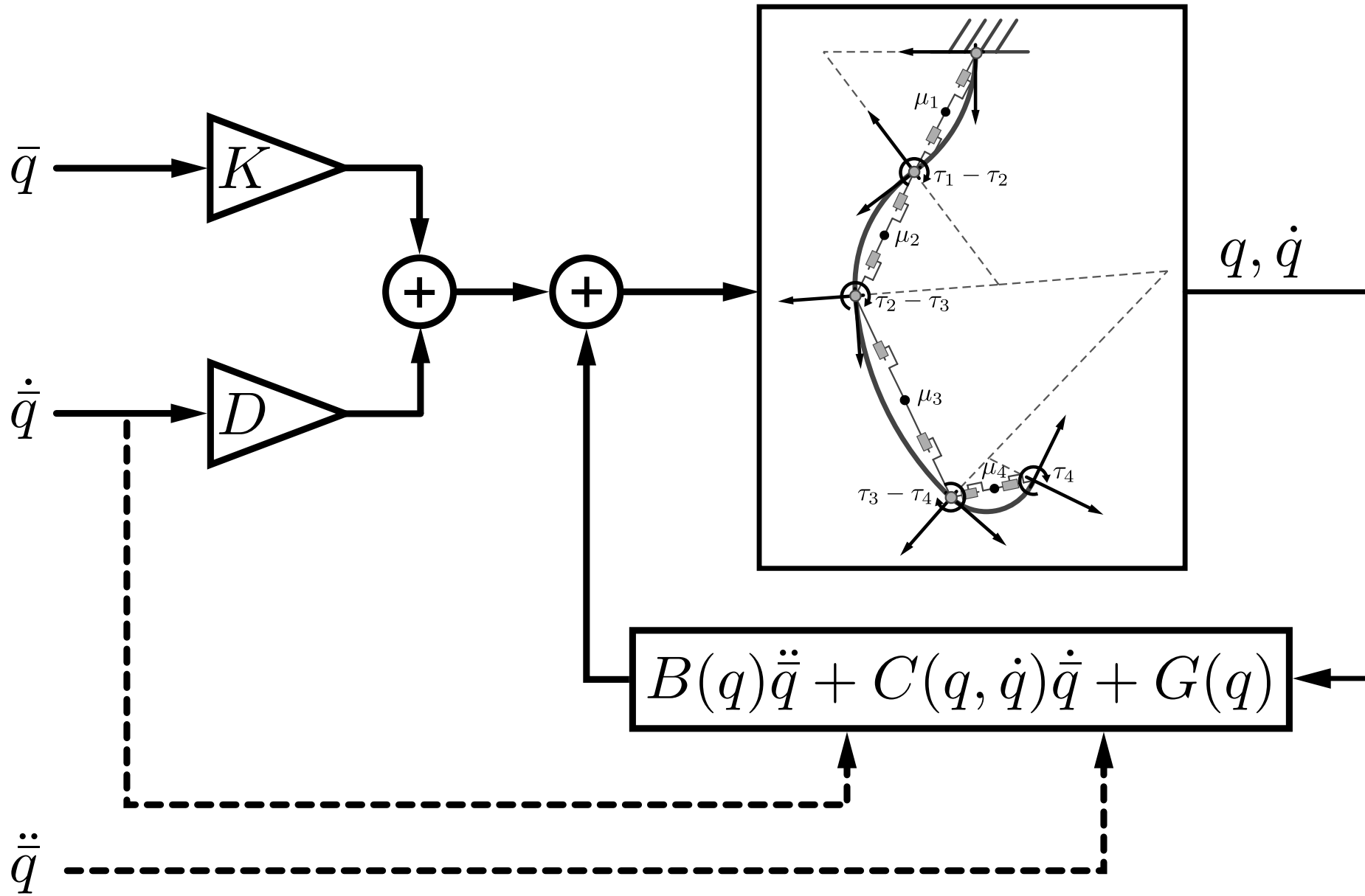
Della Santina C., et al.
"Model-based dynamic feedback control of a planar soft robot: trajectory tracking and interaction with the environment." IJRR

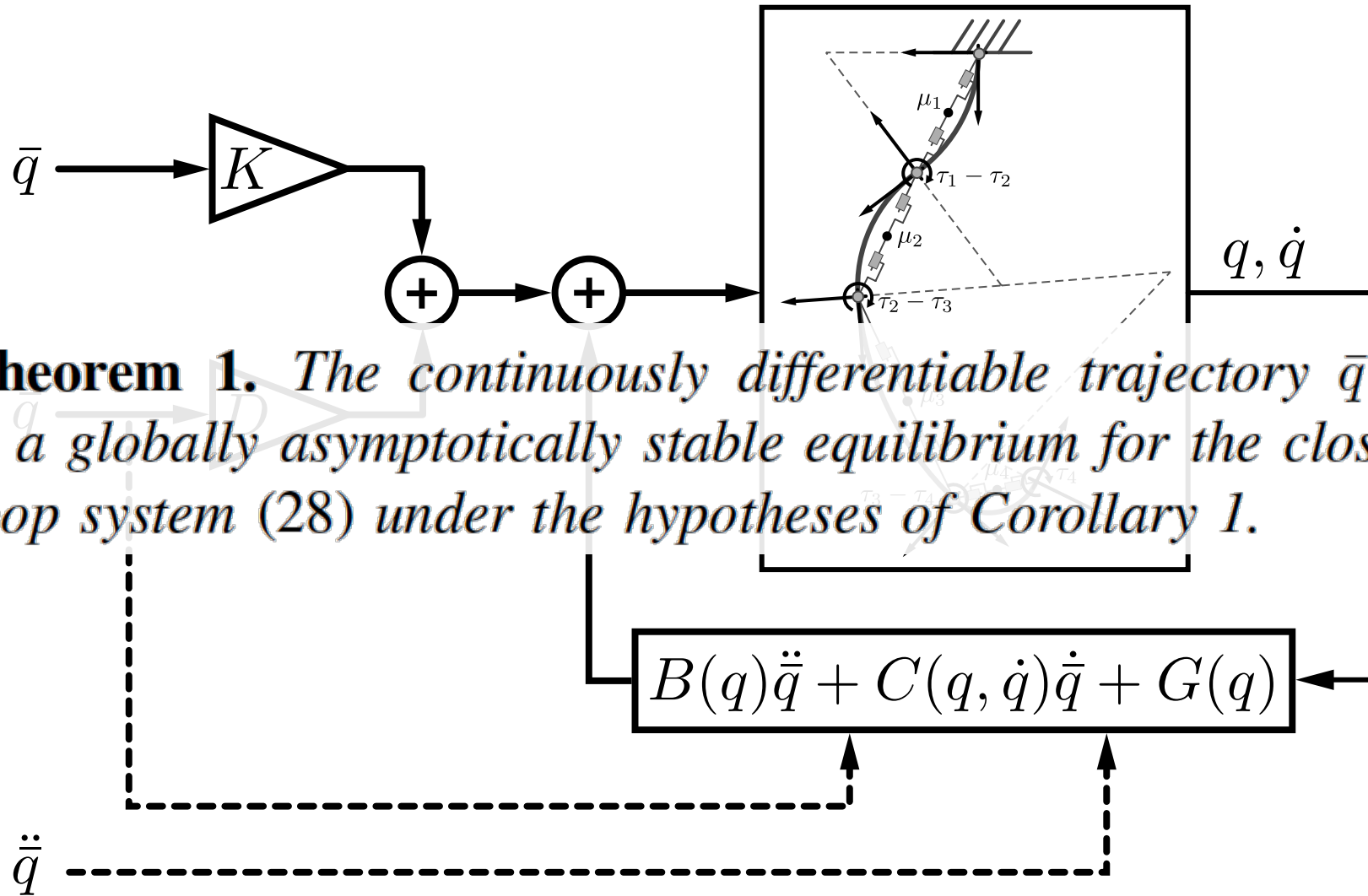
Trajectory tracking in **curvature space**

$$\dot{q} = 0$$
$$\ddot{q} = 0$$

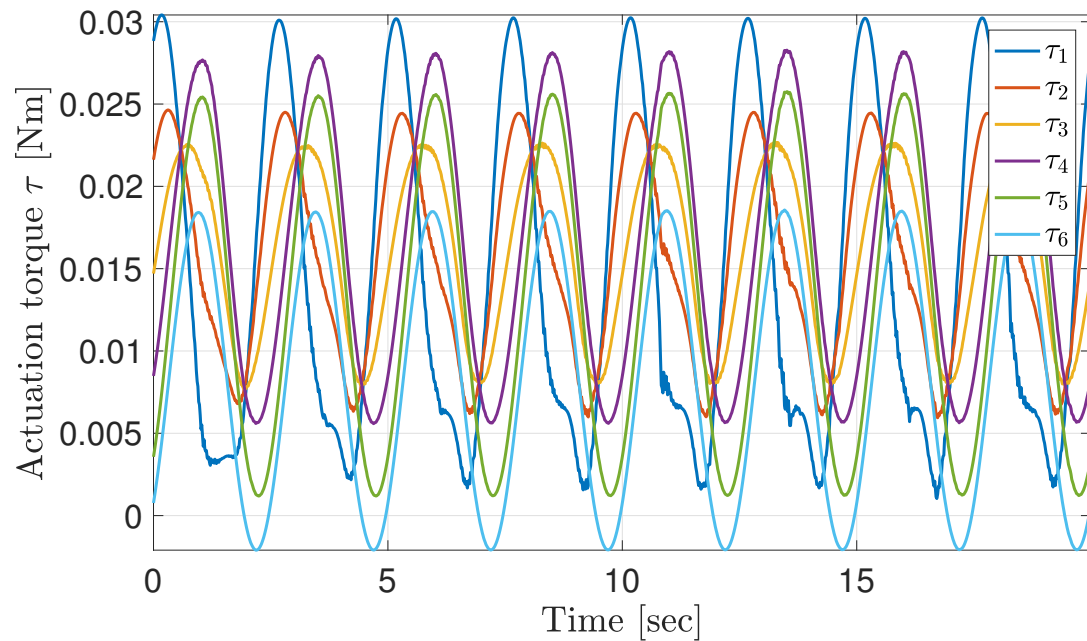
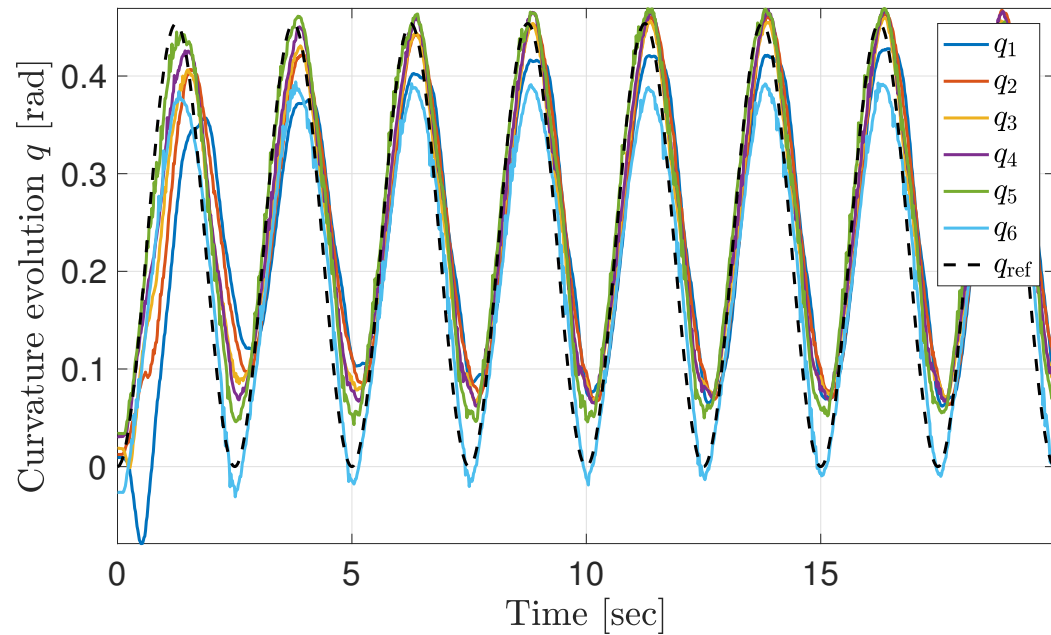


Della Santina C., et al.
"Model-based dynamic feedback control of a planar soft robot: trajectory tracking and interaction with the environment." IJRR





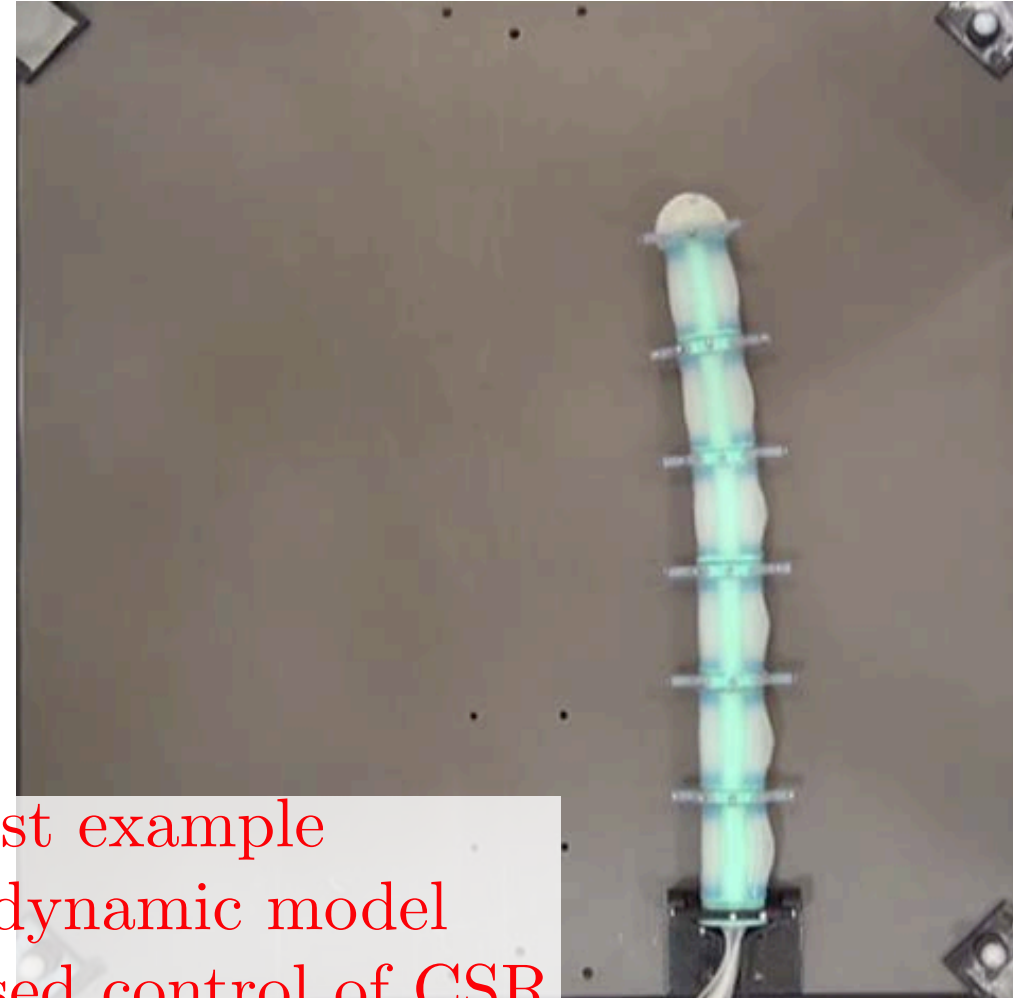
Theorem 1. *The continuously differentiable trajectory $\bar{q}(t)$ is a globally asymptotically stable equilibrium for the closed loop system (28) under the hypotheses of Corollary 1.*



$$\bar{q}_i = 13^\circ \left(1 + \cos\left(\frac{4\pi \text{ rad}}{5 \text{ s}} t\right) \right)$$

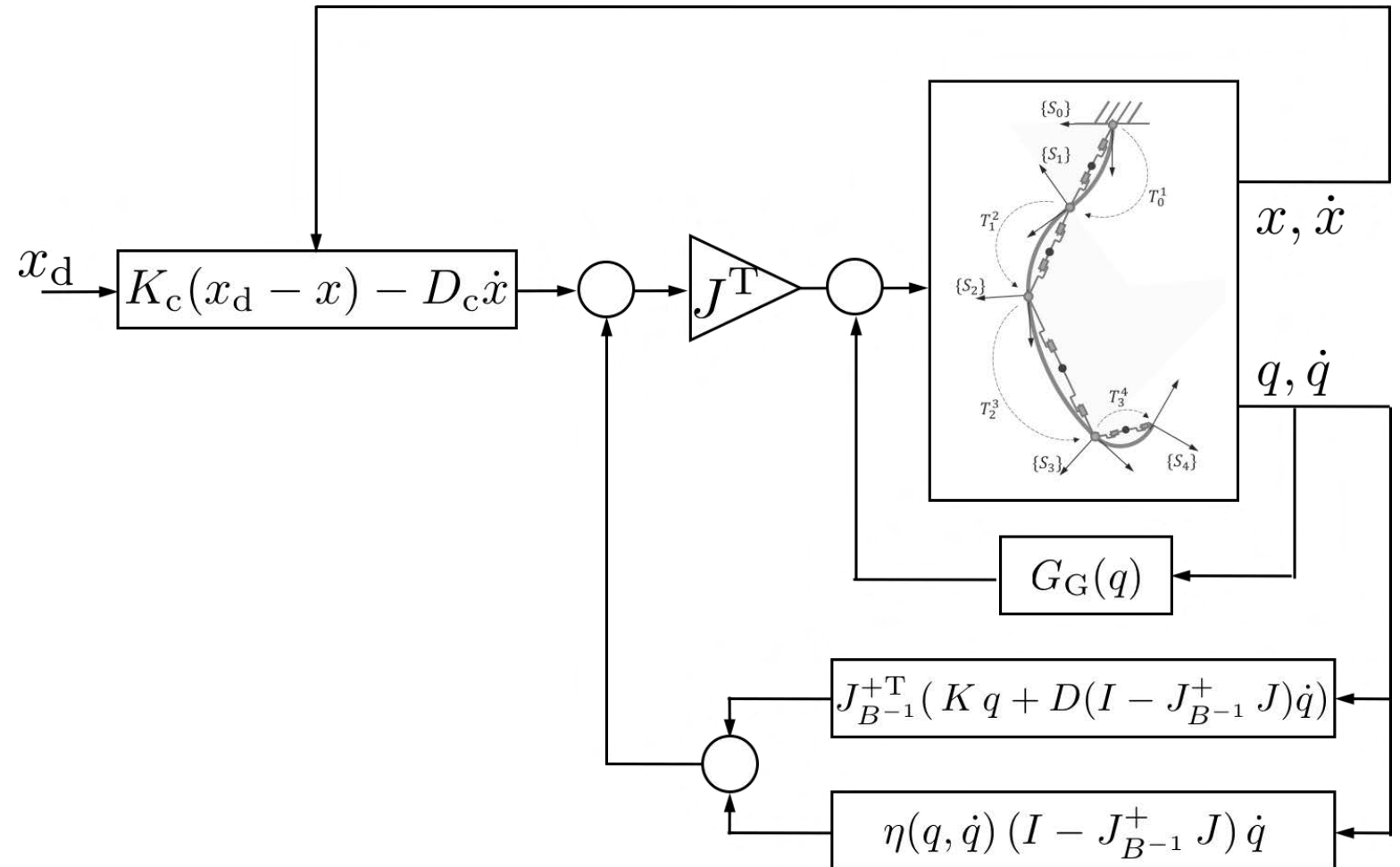
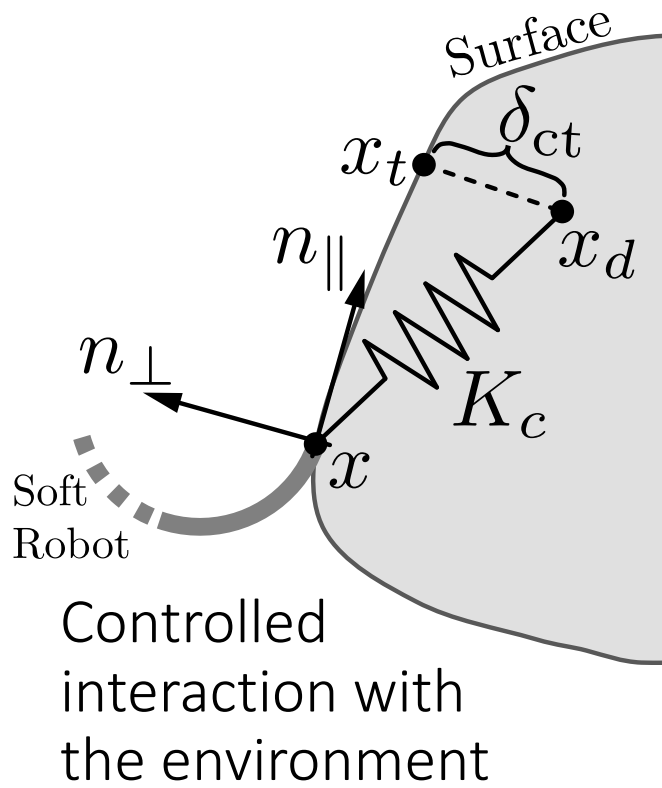
$$\forall i \in \{1, \dots, 6\}, \quad t \in [0, 20) \text{s}$$

Reference



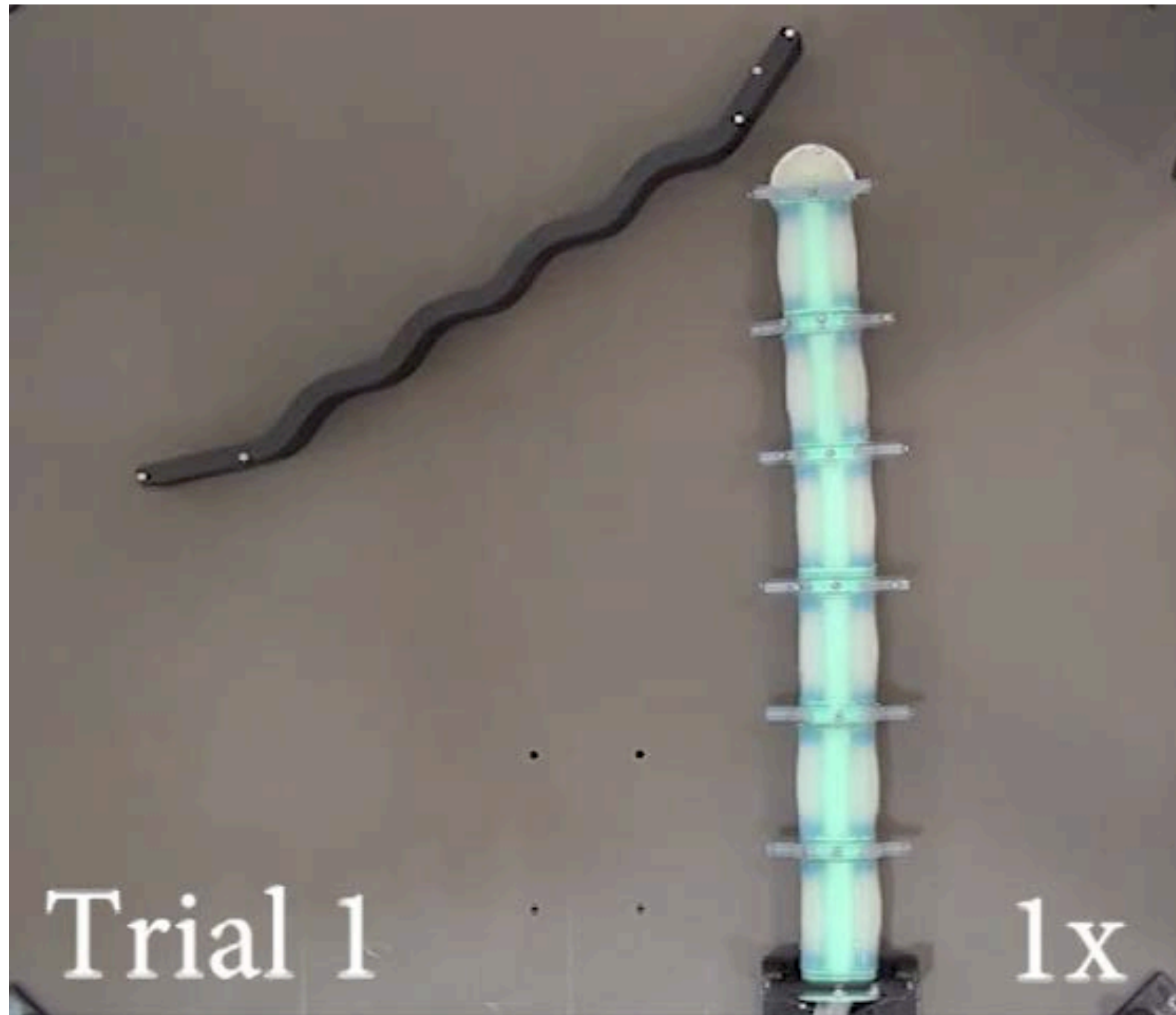
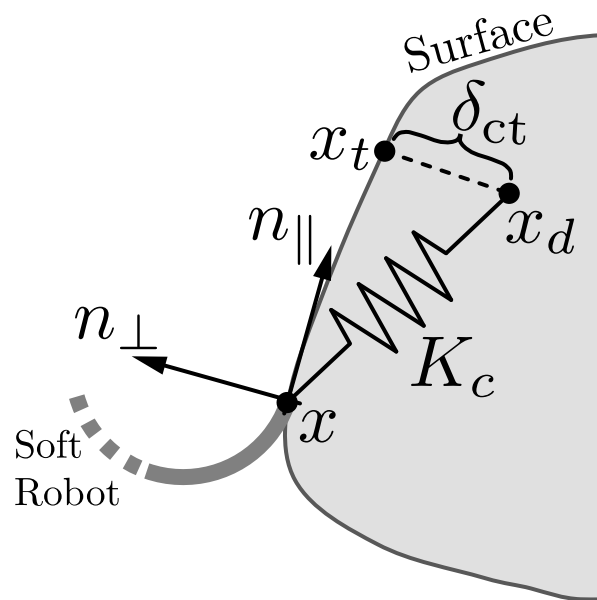
First example
of dynamic model
based control of CSR

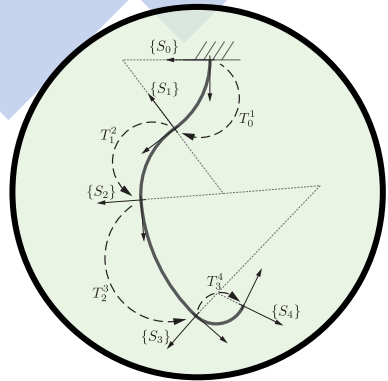
Some Cartesian impedance control too...



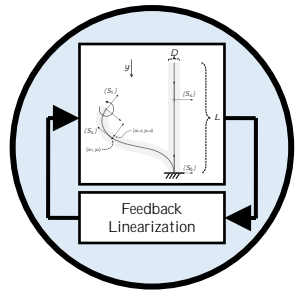
Some Cartesian impedance control too...

$$\begin{aligned}\tau = & J^T(q)J_B^{+T}(q)(Kq + D\dot{q}) + G(q) \\ & + J^T(q)\eta(q, \dot{q})(I - J_B^+(q)J(q))\dot{q} \\ & + J^T(q)(K_c(x_d - x) - D_cJ(q)\dot{q}),\end{aligned}$$

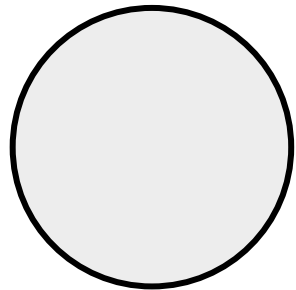




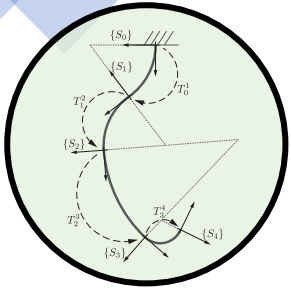
Feedback Model Based Control Is Robust to Rough Approximations



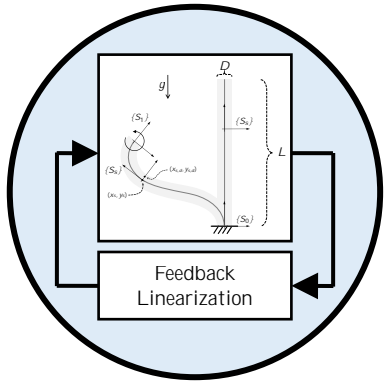
If You Want to Dig More
Do That in a Control Oriented Way



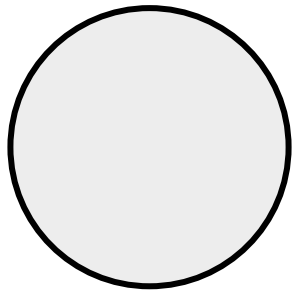
If You Want to Stick to the Simple Model,
Consider Control-Driven Ways to Improve It



Feedback Model Based Control
Is Robust to Rough Approximations



If You Want to Dig More
Do That in a Control Oriented Way



If You Want to Stick to the Simple Model,
Considered Control-Driven Ways to Improve It

Side View



Reduced performance

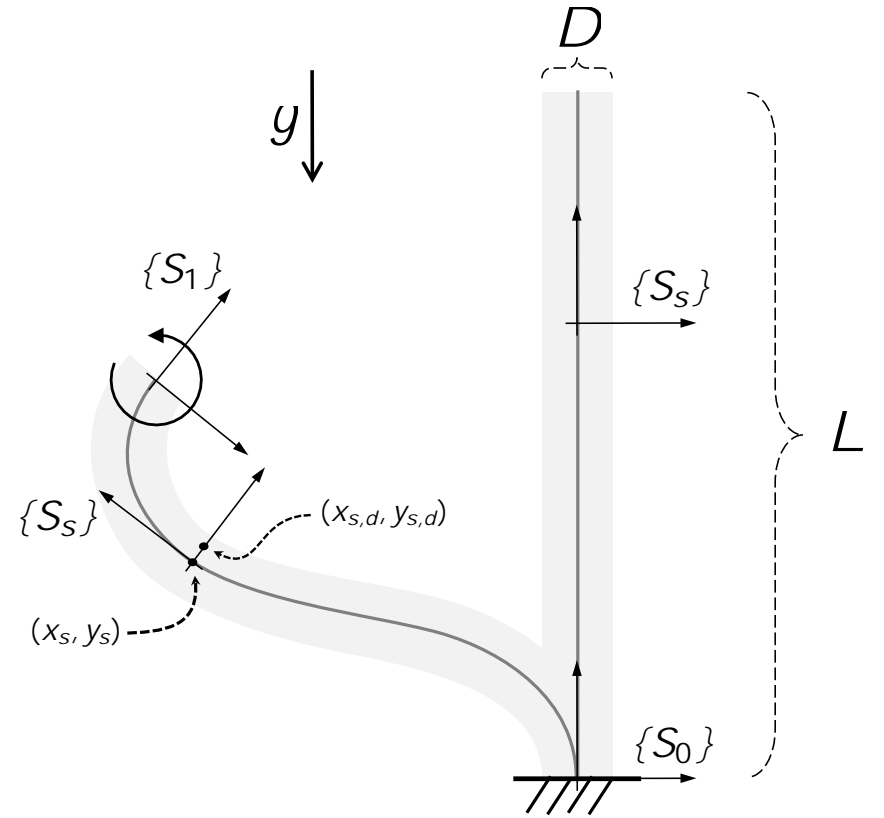
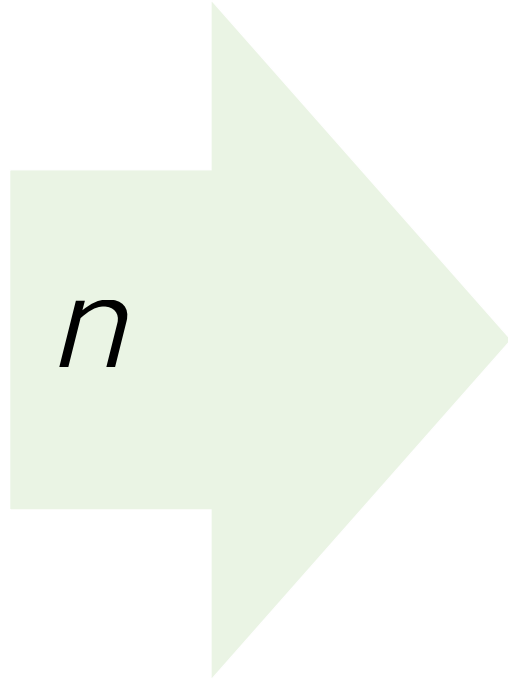
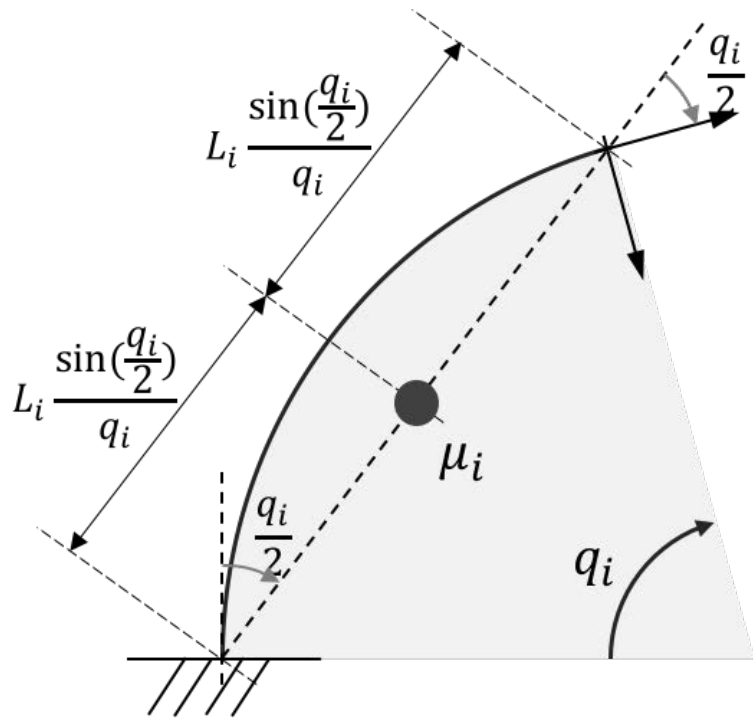


Persistent oscillations

Why does it work?

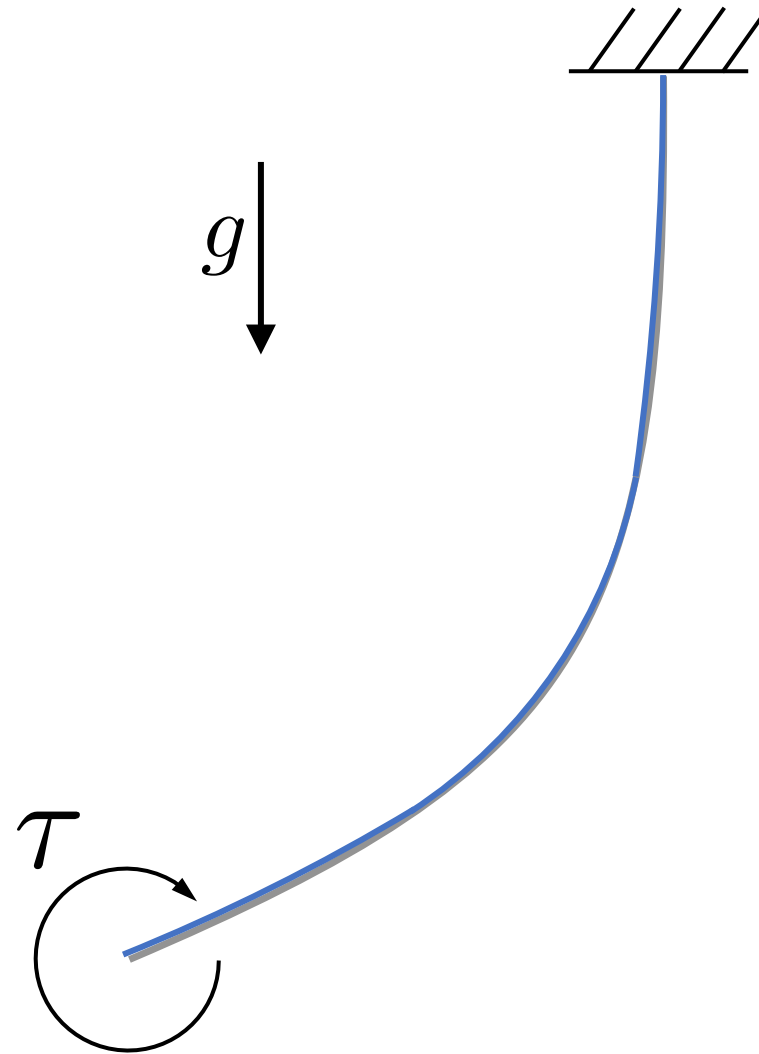


What to correct it when it does not work?



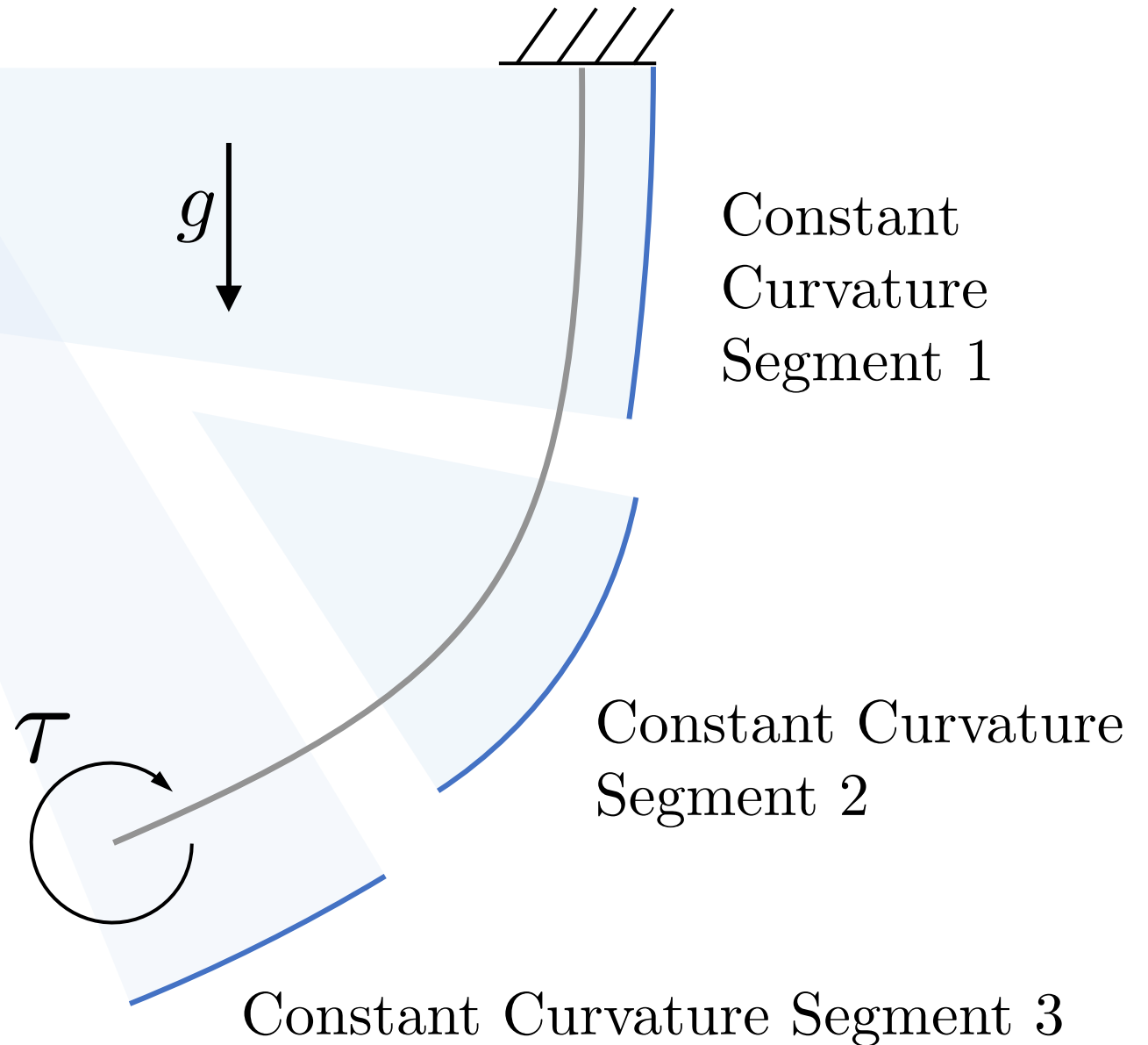
To Infinity and Beyond

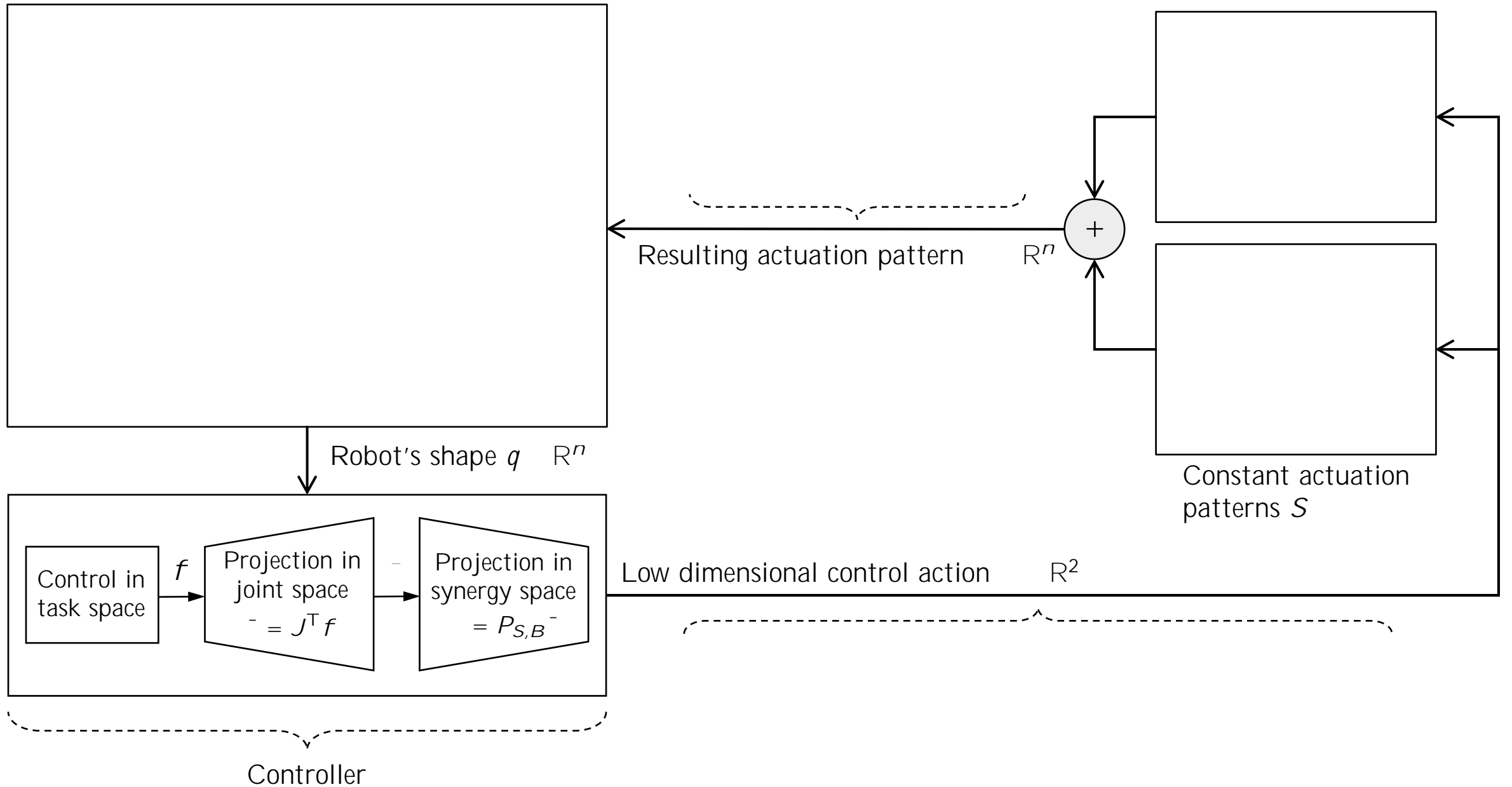
What to do?



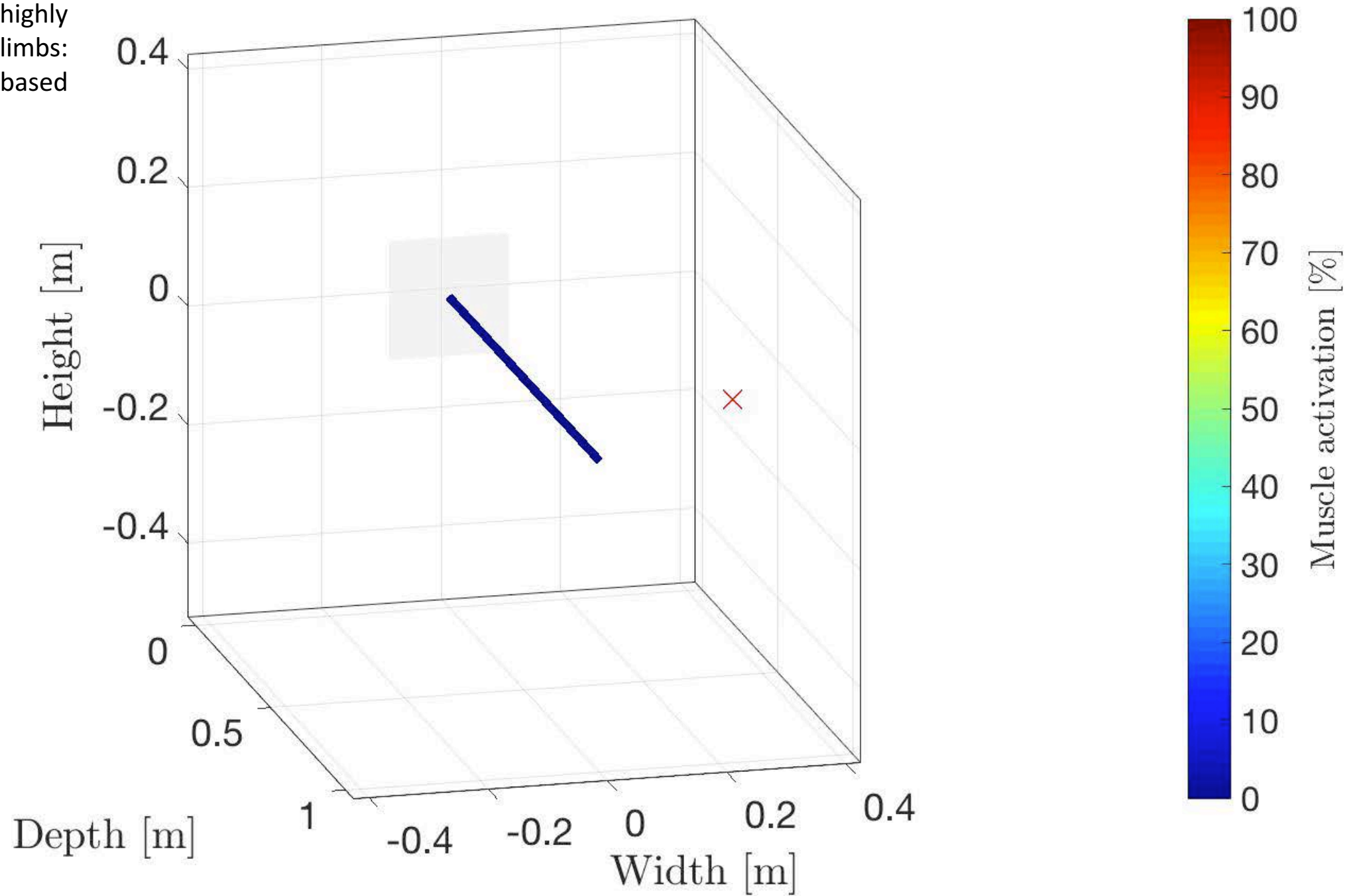
What to do?

Just take a less
coarse discretization!

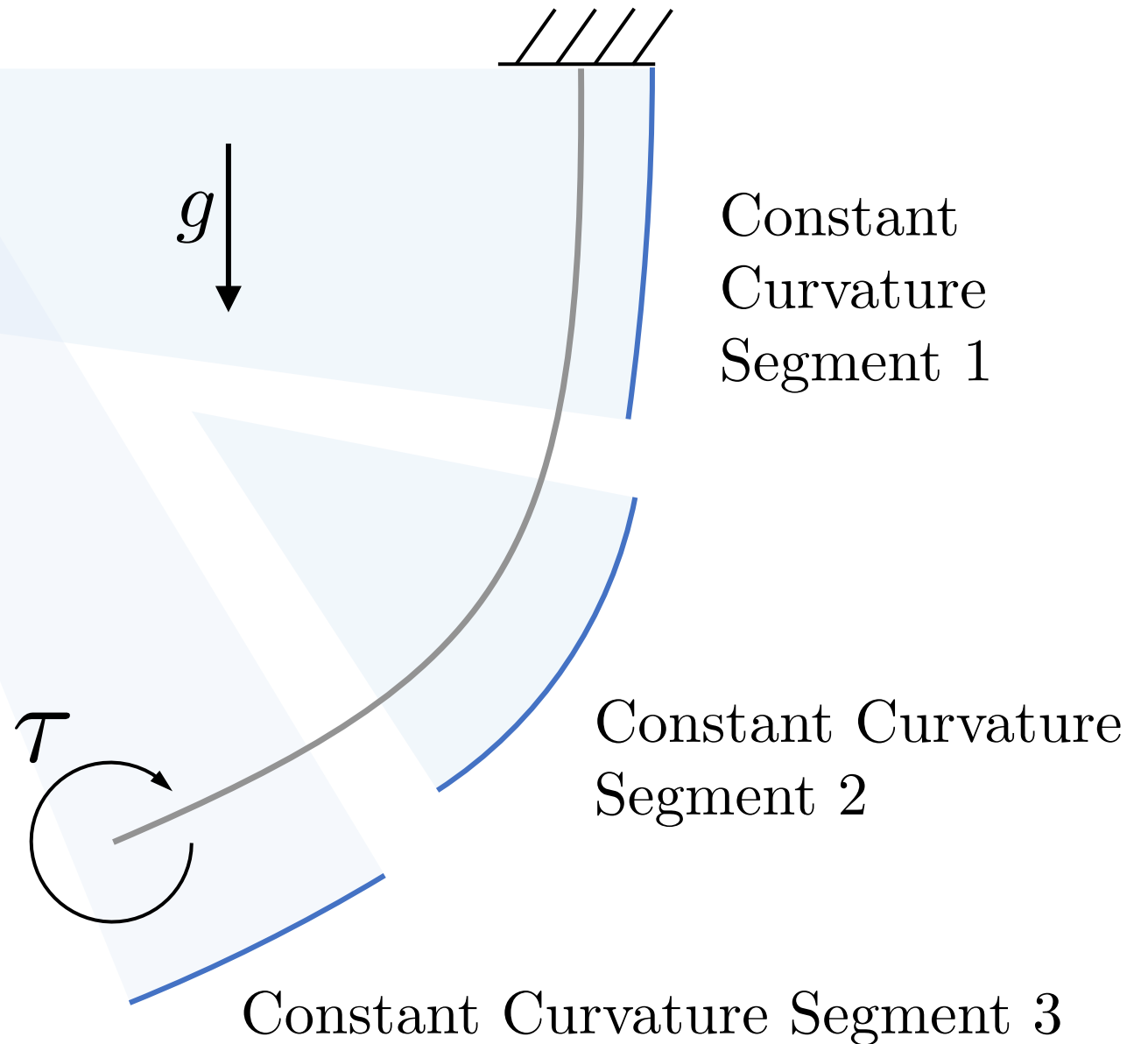
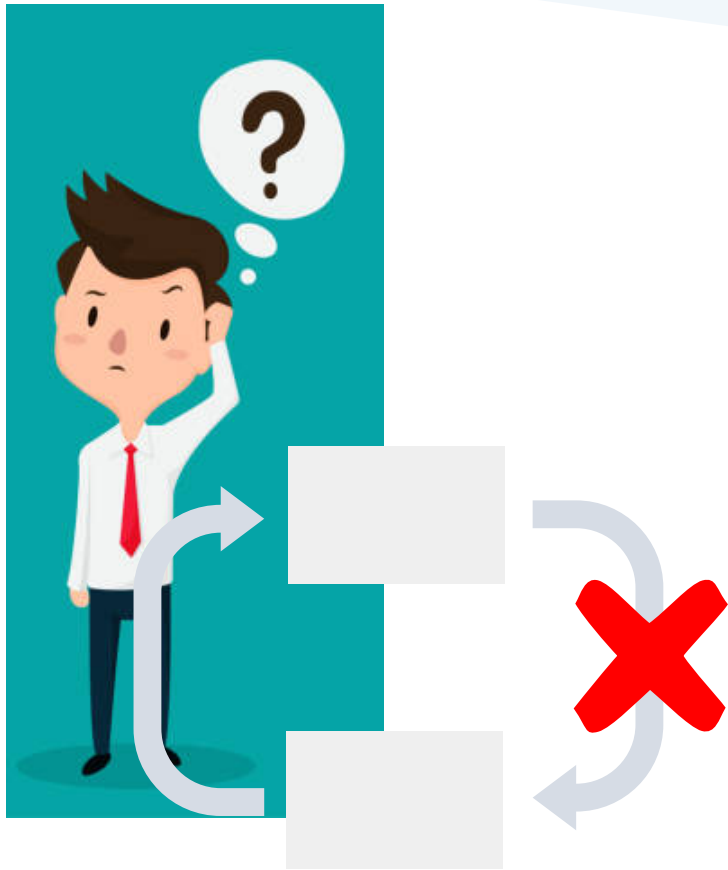




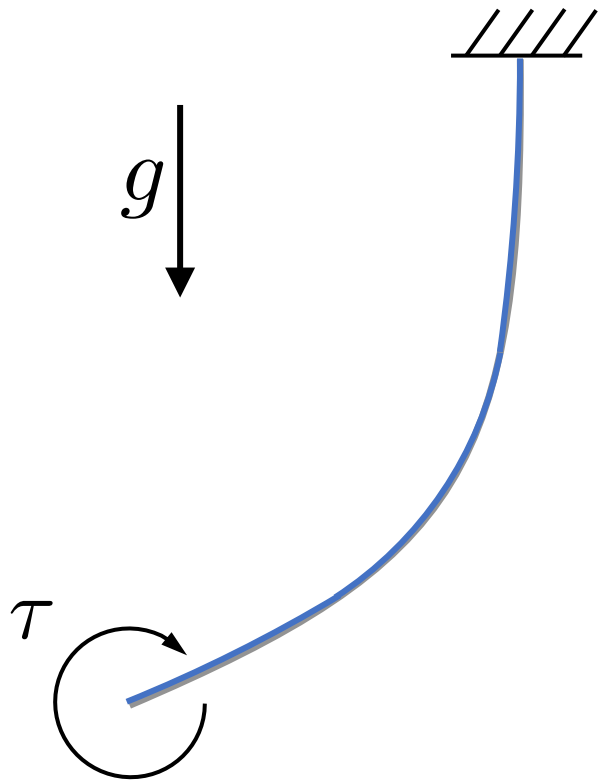
Della Santina et al. "Exact task execution in highly under-actuated soft limbs: an operational space based approach" *RAL 2019*



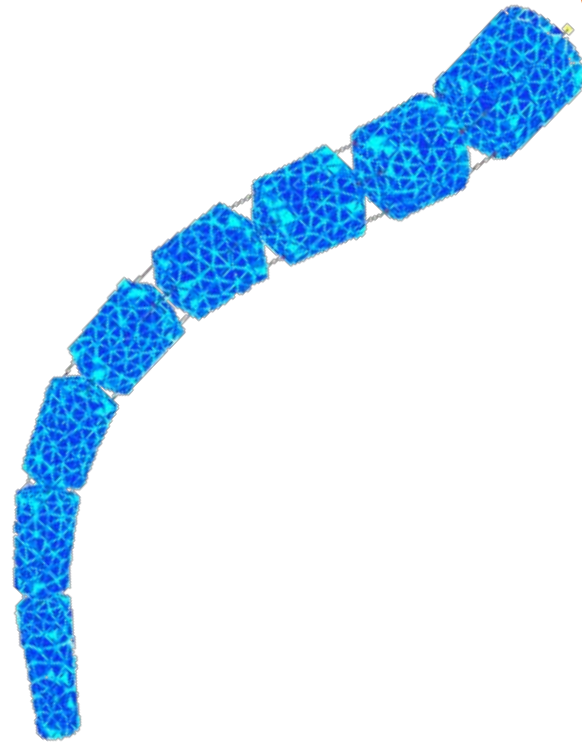
Just take a less
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Just take a less
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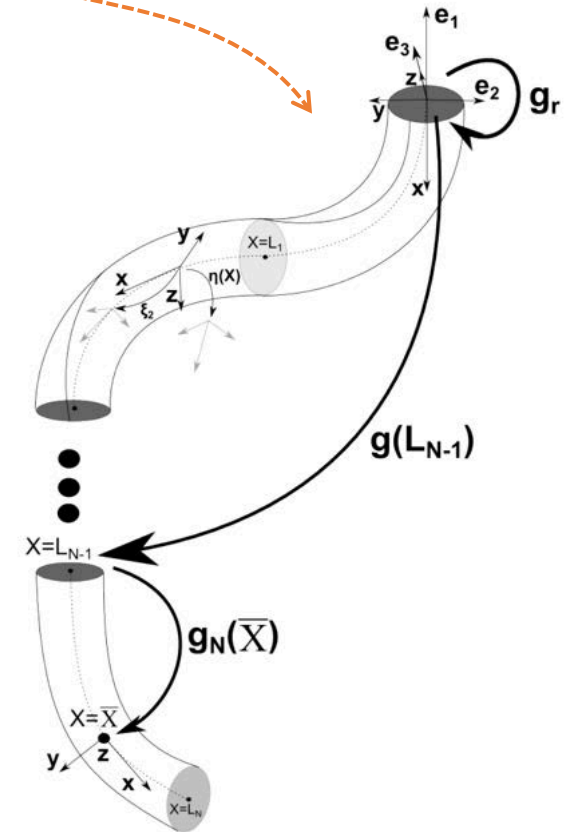


Della Santina et al. "Exact task execution in highly under-actuated soft limbs: an operational space based approach" *RAL* 2019



Coevoet et al. "Software toolkit for modeling, simulation and control of soft robots" *Advanced Robotics* 2017

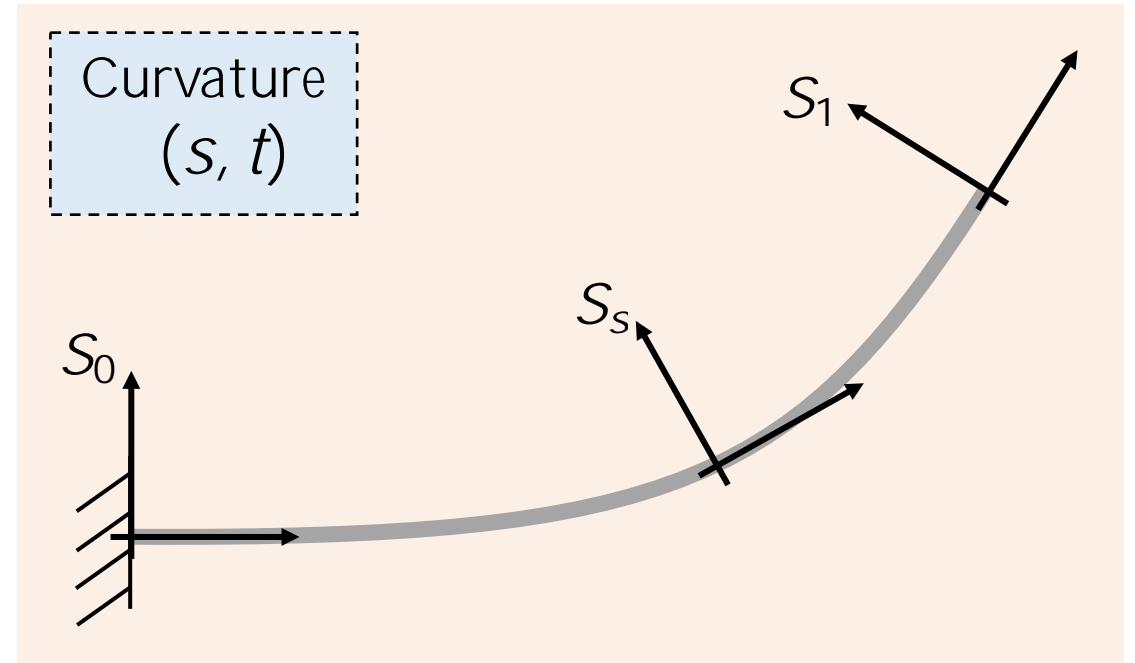
Quite advanced!



Renda et al. "Discrete Cosserat Approach for Multi-Section Soft Robots Dynamics" *TRO* 2016

Kinematics

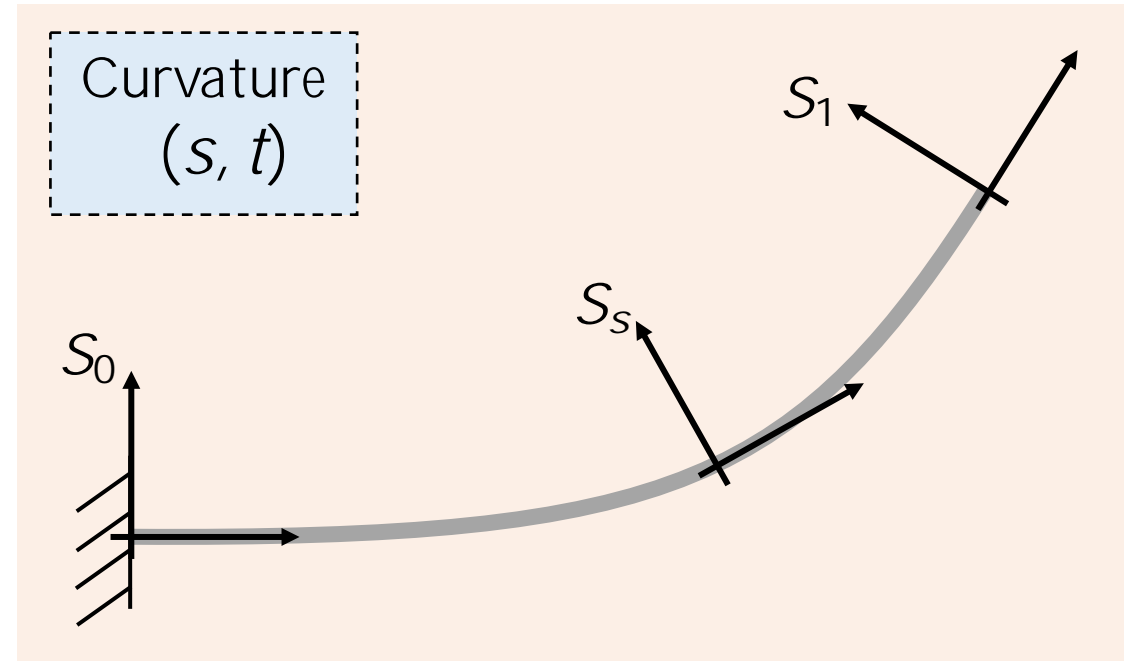
Configuration space



Kinematics

Configuration space

Hypothesis:
is analytical in s

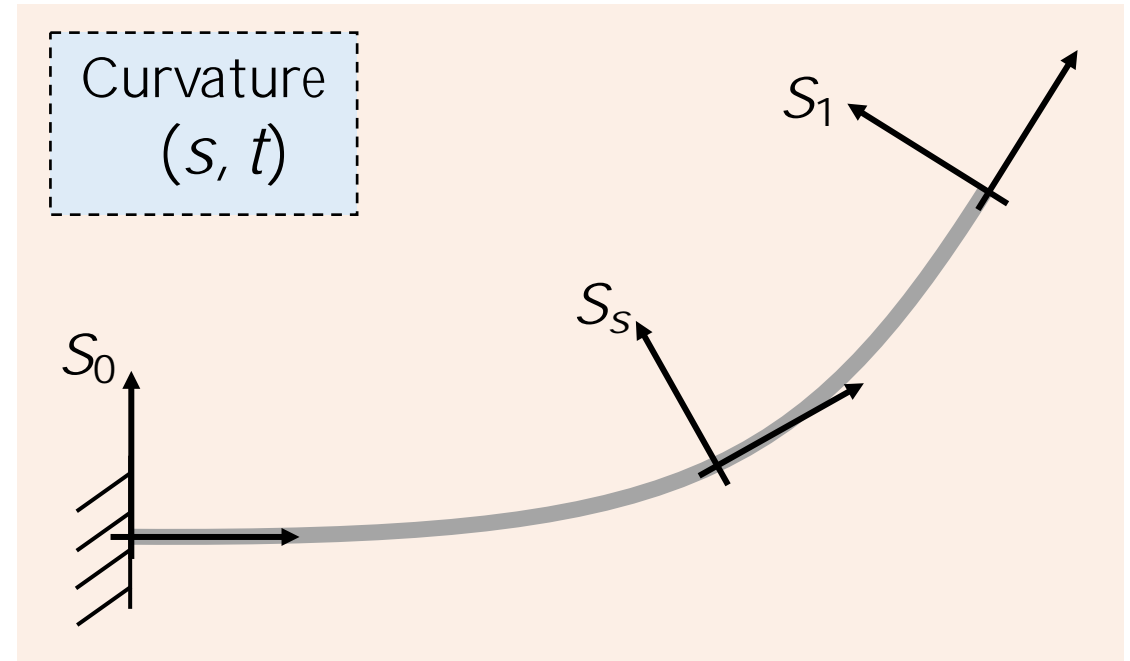


Kinematics

Configuration space

Hypothesis:
is analytical in s

$$(s, t) = \sum_{i=0} s^i(t)$$

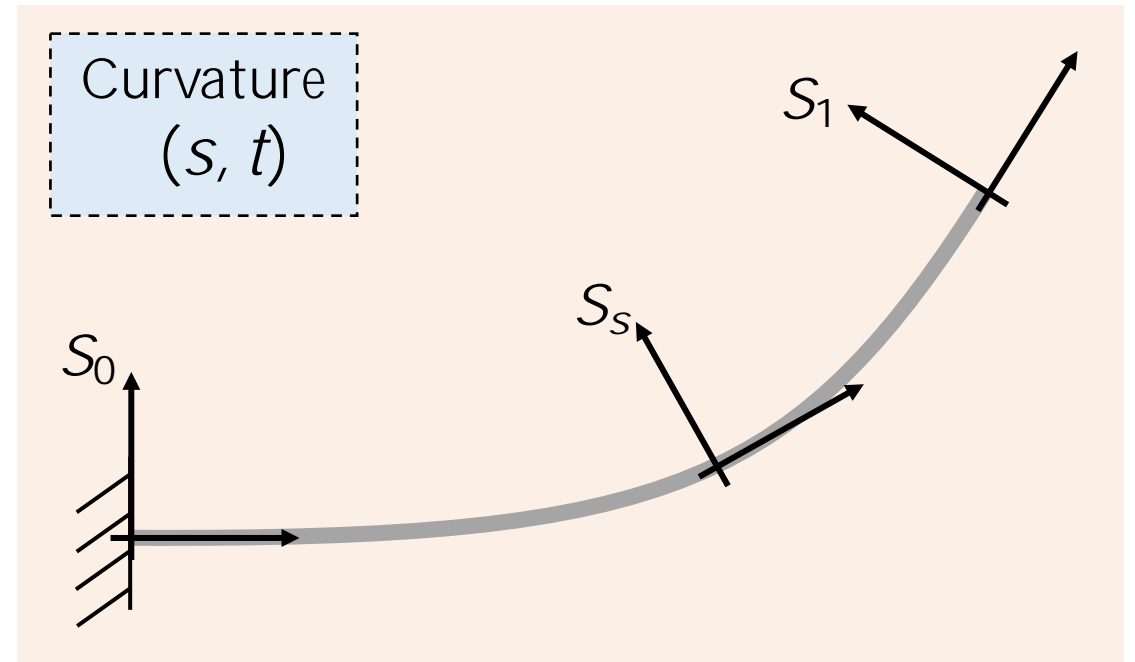


Kinematics

Configuration space

Hypothesis:
is analytical in s

$$(s, t) = \sum_{i=0}^m c_i(t) s^i$$



Polynomial Curvature!!!

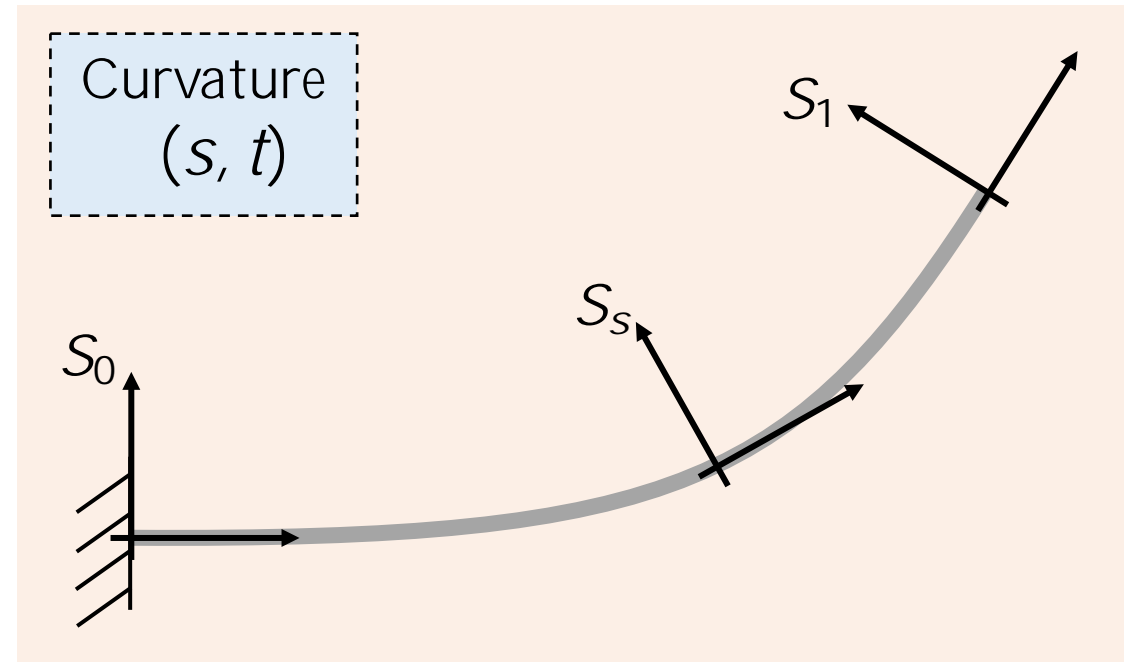
$$(s, t) = \sum_{i=0}^m c_i(t) s^i$$

Kinematics

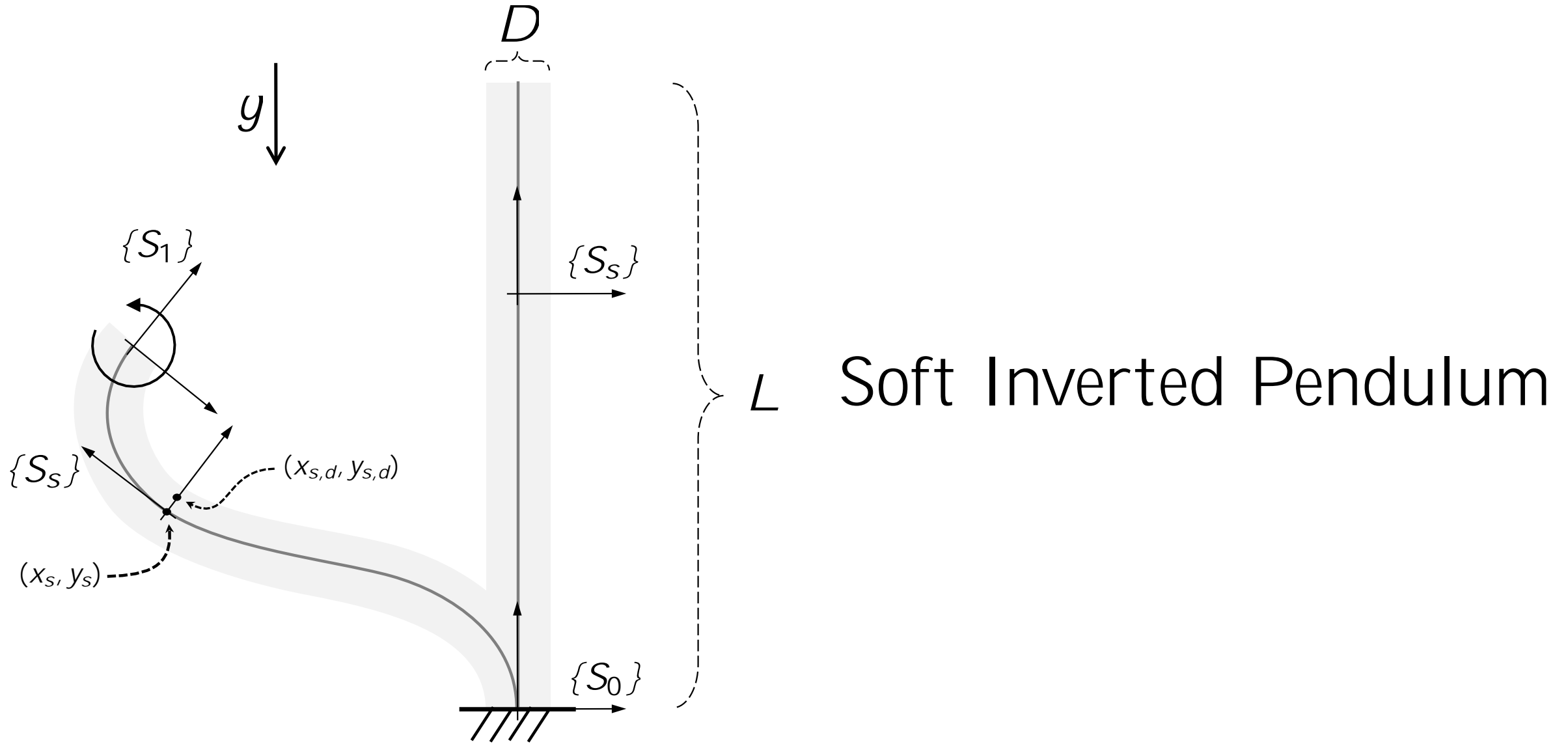
Configuration space

Hypothesis:
is analytical in s

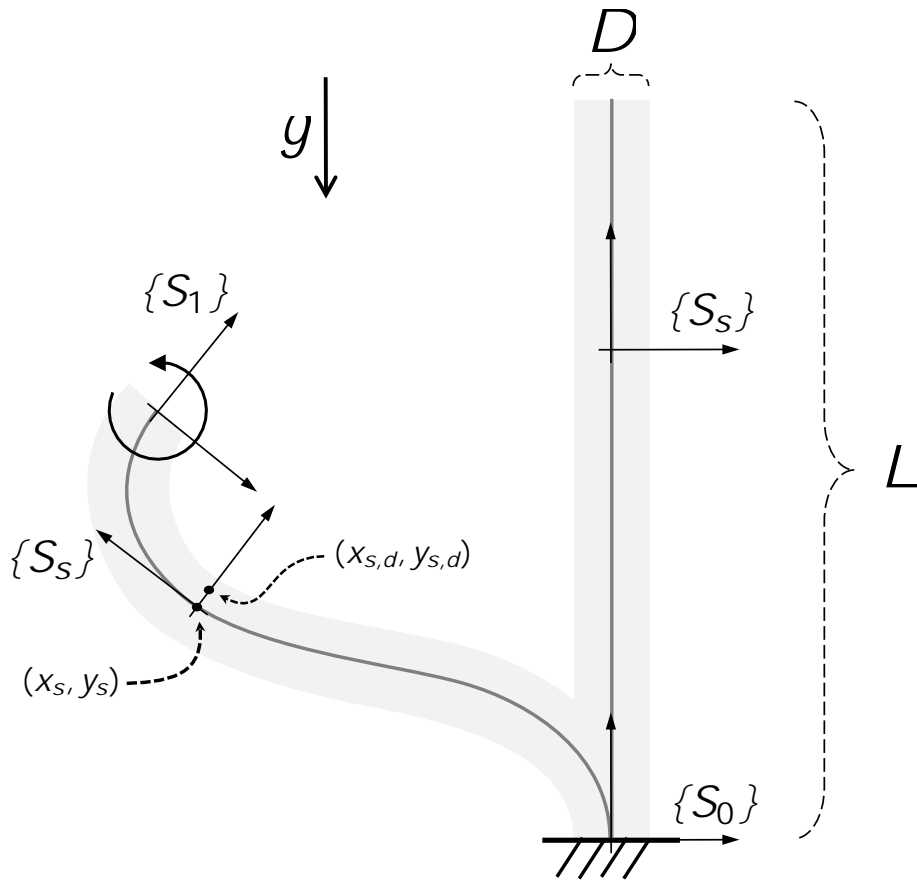
$$(s, t) = \sum_{i=0}^m i(t) s^i$$



$$(s, t) = \sum_{i=0}^m i(t) s^i$$

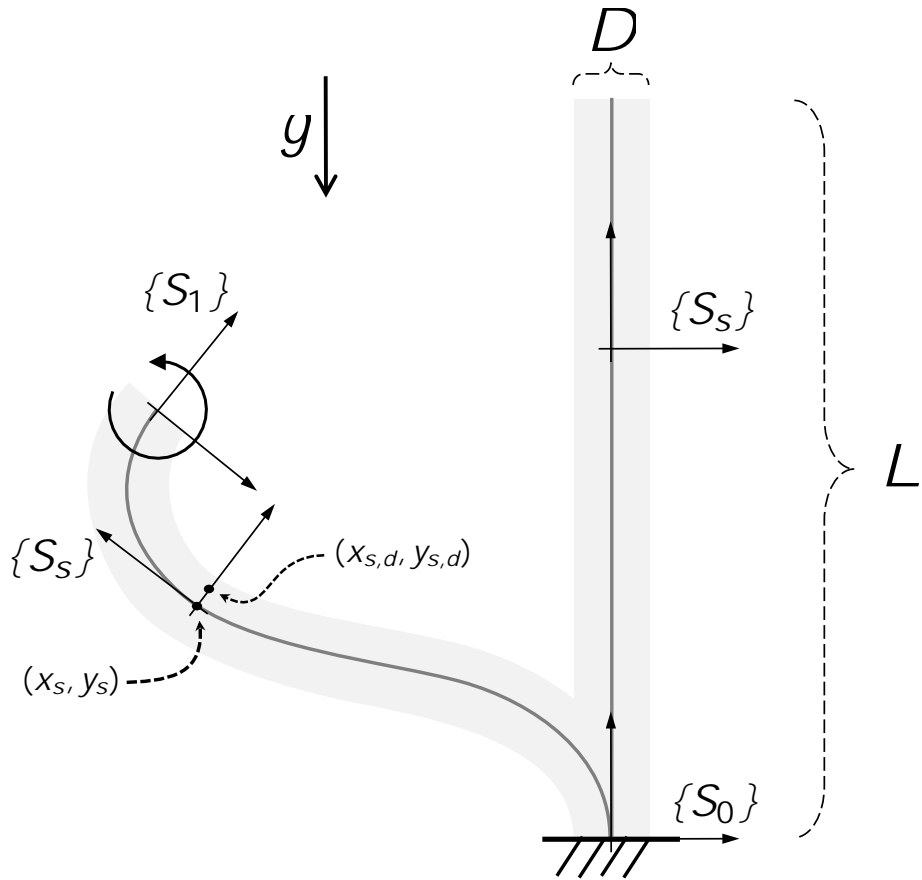


$$\tilde{B}(q)\ddot{q} + \tilde{C}(q, \dot{q})\dot{q} + \tilde{G}(q) + \tilde{K}q + \tilde{D}\dot{q} = 0$$

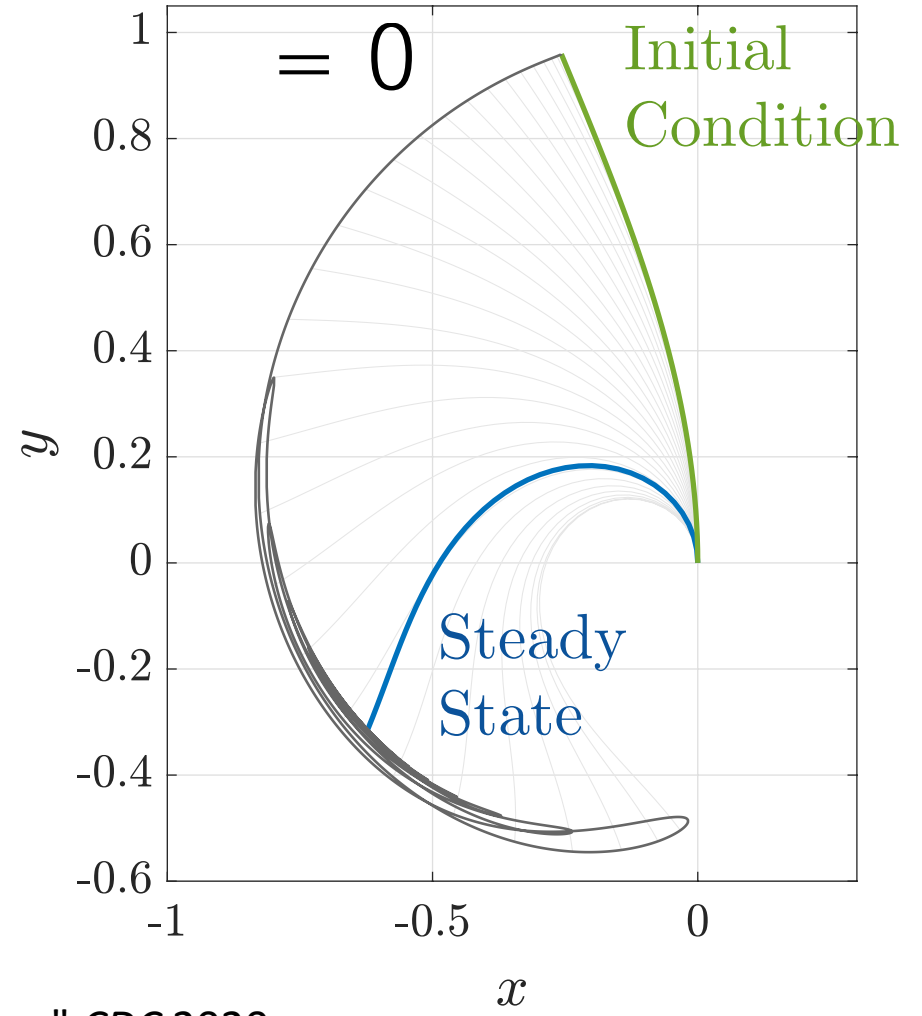


Soft Inverted Pendulum

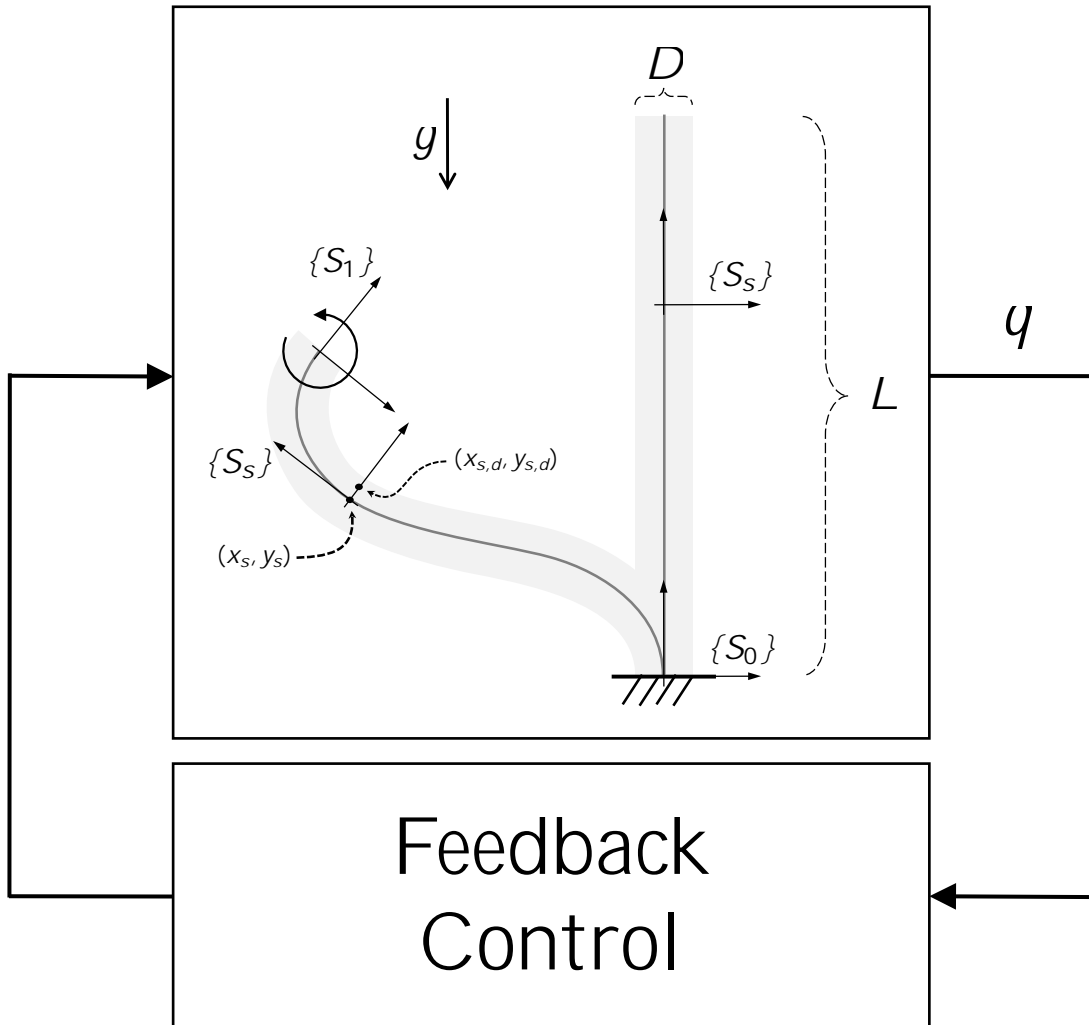
$$\tilde{B}(q)\ddot{q} + \tilde{C}(q, \dot{q})\dot{q} + \tilde{G}(q) + \tilde{K}q + \tilde{D}\dot{q} = 0$$



Soft Inverted Pendulum

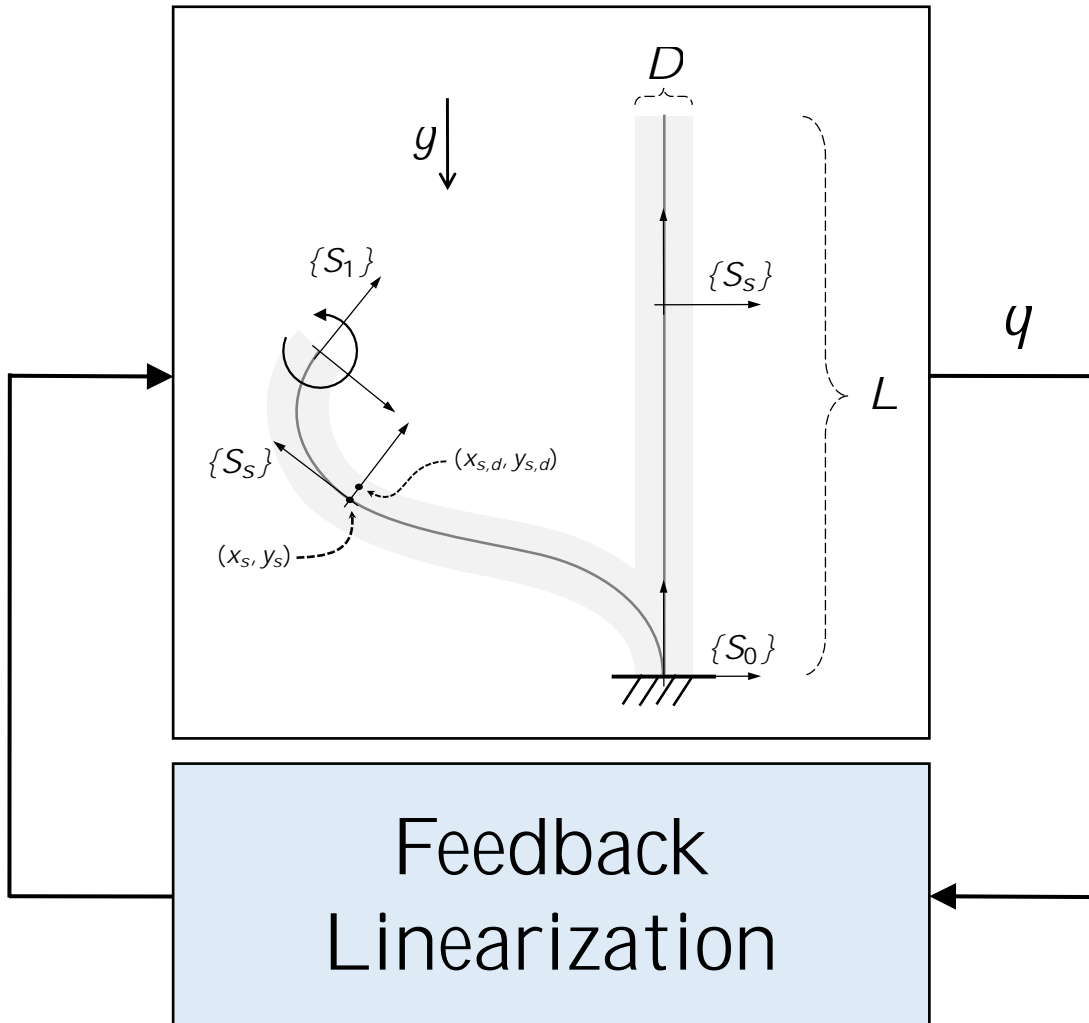


$$\tilde{B}(q)\ddot{q} + \tilde{C}(q, \dot{q})\dot{q} + \tilde{G}(q) + \tilde{K}q + \tilde{D}\dot{q} = 0$$



Della Santina, Cosimo.
 "The Soft Inverted
 Pendulum with Affine
 Curvature." *CDC 2020*

$$\tilde{B}(q)\ddot{q} + \tilde{C}(q, \dot{q})\dot{q} + \tilde{G}(q) + \tilde{K}q + \tilde{D}\dot{q} = 0$$



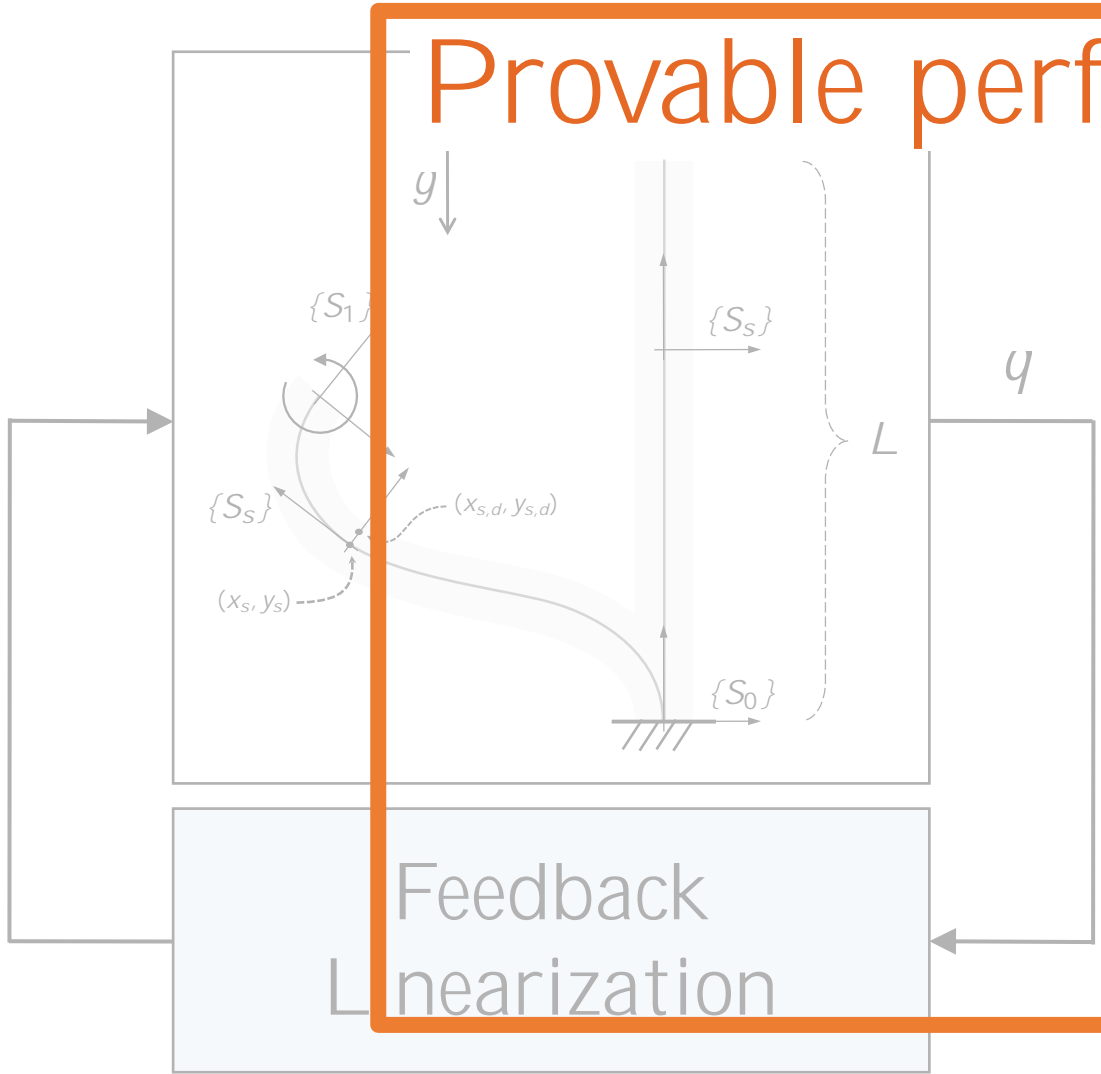
$$= h_1 - (\tilde{B}_{2,1}/\tilde{B}_{2,2})h_2$$

$$- \tilde{B}_{1,1} - \tilde{B}_{2,1}^2/\tilde{B}_{2,2} (Pq_0 + D\dot{q}_0)$$

Della Santina, Cosimo.
 "The Soft Inverted
 Pendulum with Affine
 Curvature." *CDC 2020*

$$\tilde{B}(q)\ddot{q} + \tilde{C}(q, \dot{q})\dot{q} + \tilde{G}(q) + \tilde{K}q + \tilde{D}\dot{q} = 0$$

Provable performance!

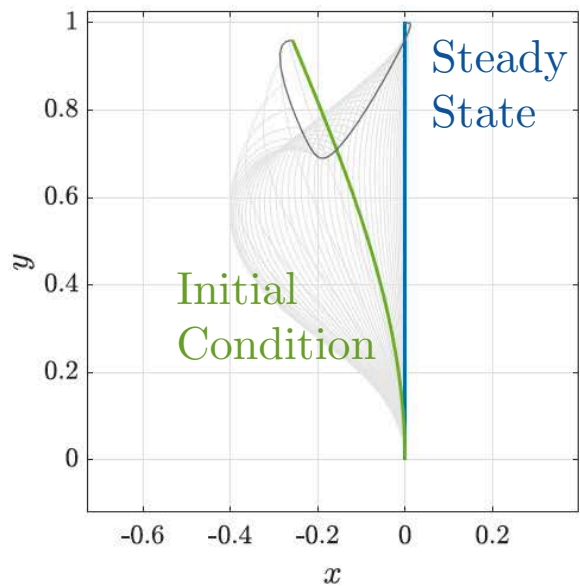


$$= h_1 - (\tilde{B}_{2,1}/\tilde{B}_{2,2})h_2$$

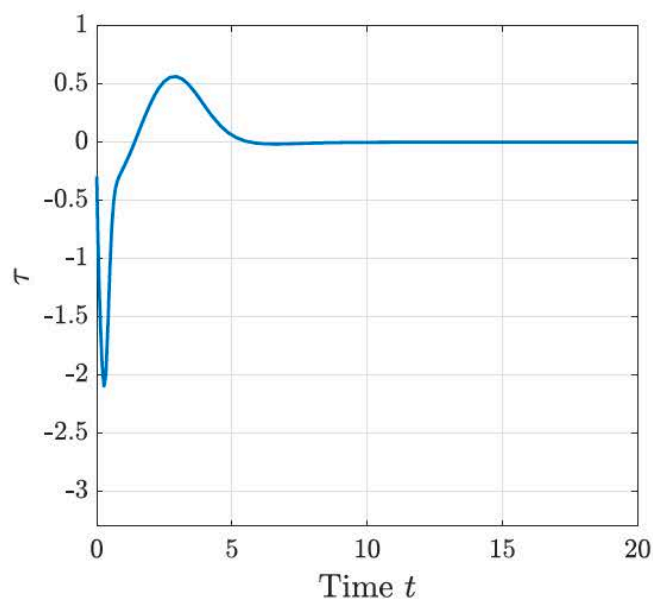
$$- \tilde{B}_{1,1} - \tilde{B}_{2,1}^2/\tilde{B}_{2,2} (Pq_0 + D\dot{q}_0)$$

Della Santina, Cosimo.
 "The Soft Inverted
 Pendulum with Affine
 Curvature." CDC 2020

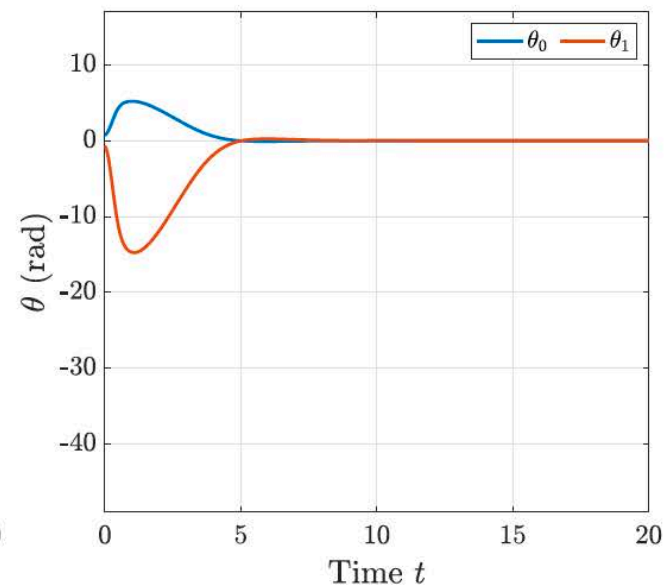
Example 1



(a) Pendulum, $k = 0.25$

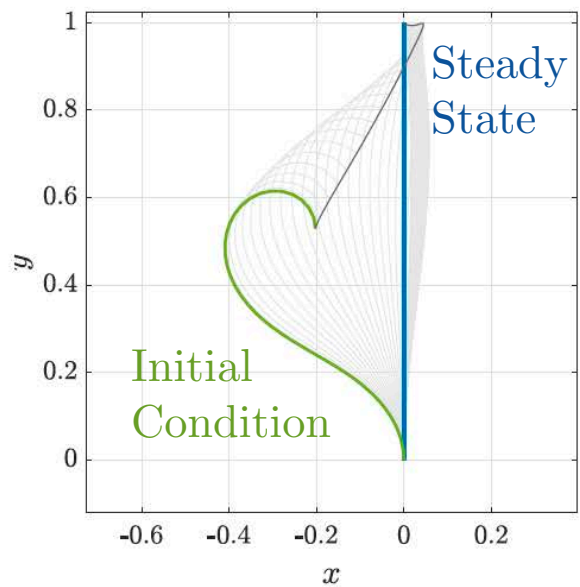


(b) Control action, $k = 0.25$

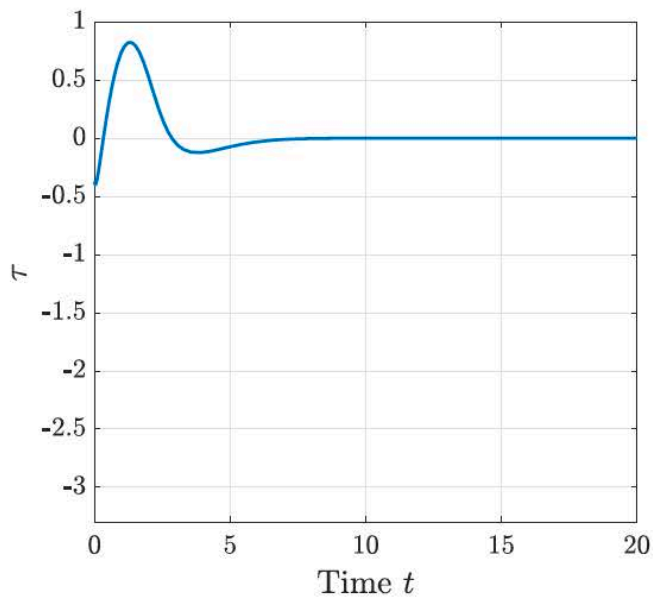


(c) Natural config., $k = 0.25$

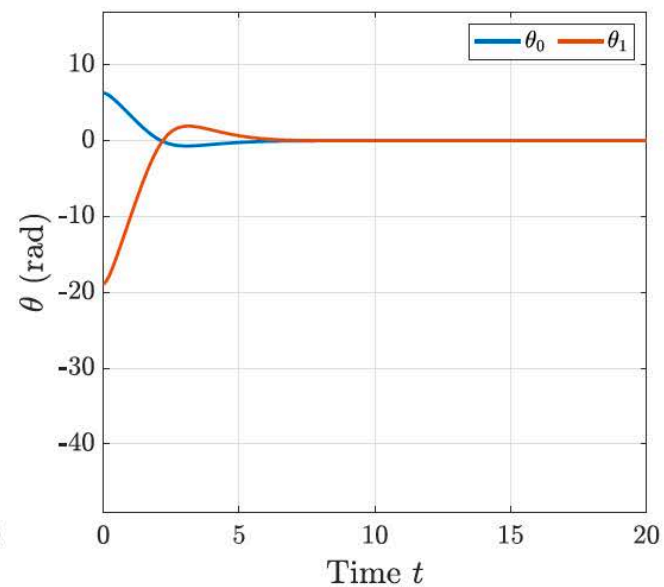
Example 2



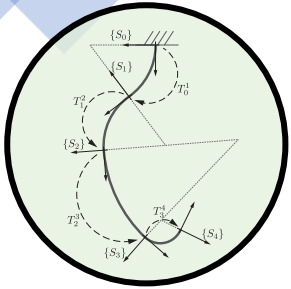
(e) Pendulum, $k = 0.25$, far



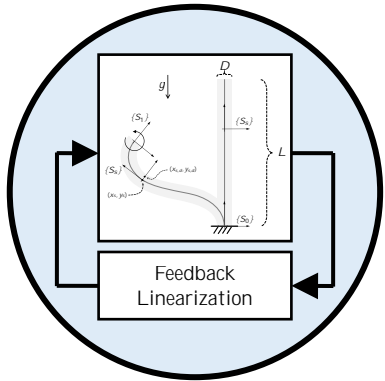
(f) Control action, $k = 0.25$, far



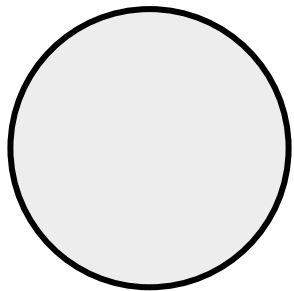
(g) Natural config., $k = 0.25$, far



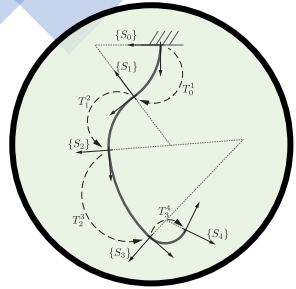
Feedback Model Based Control
Is Robust to Rough Approximations



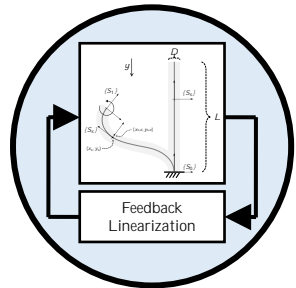
If You Want to Dig More
Do That in a Control Oriented Way



If You Want to Stick to the Simple Model,
Considered Control-Driven Ways to Improve It



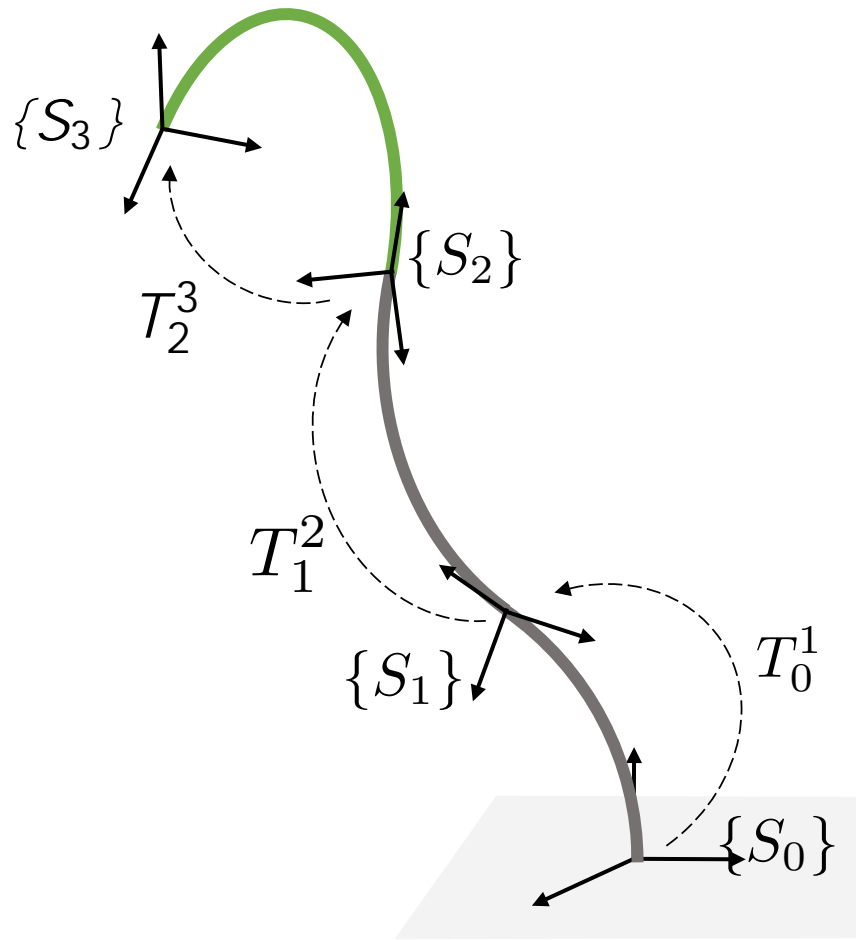
Feedback Model Based Control
Is Robust to Rough Approximations



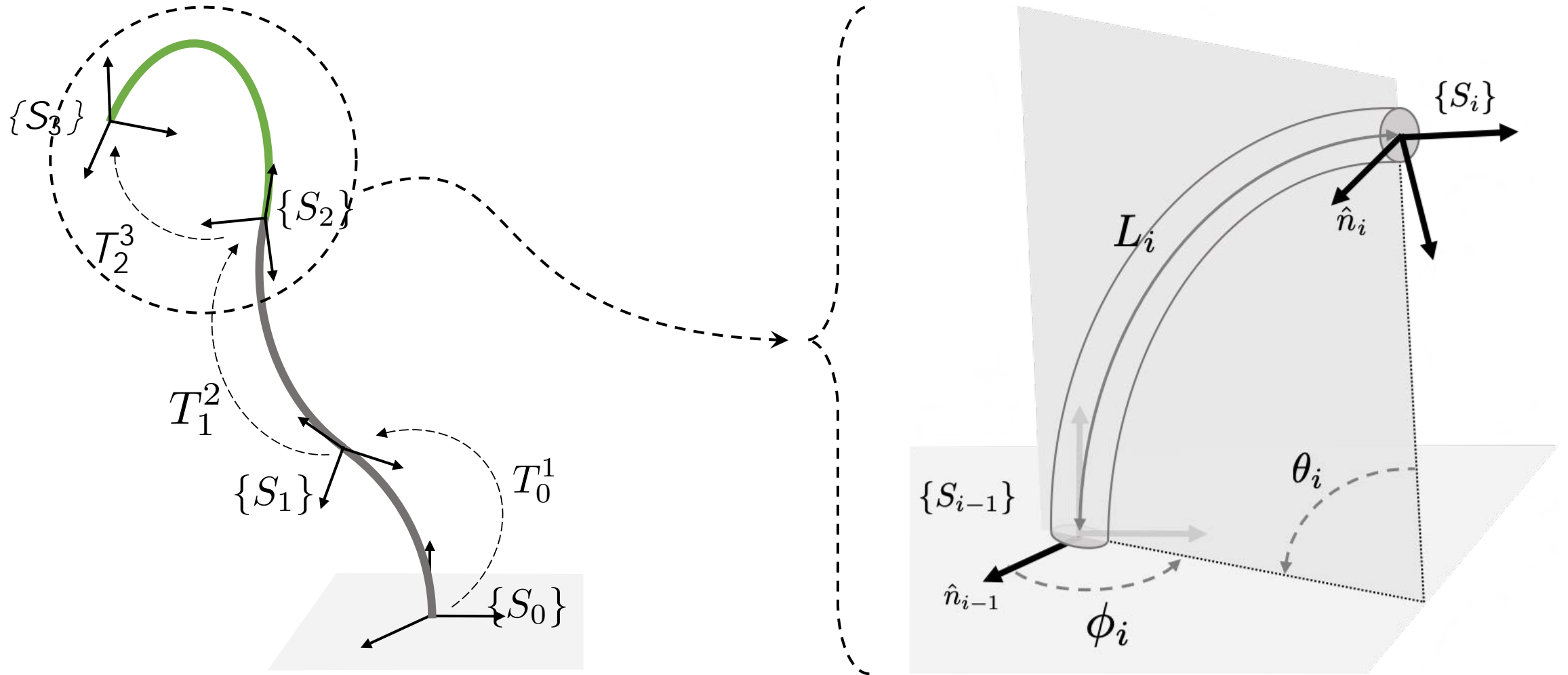
If You Want to Dig More
Do That in a Control Oriented Way

If You Want to Stick to the Simple Model,
Considered Control-Driven Ways to Improve It

Standard Extension of PCC to 3D (kinematics)



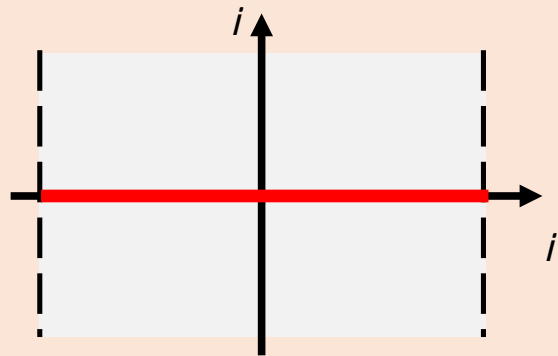
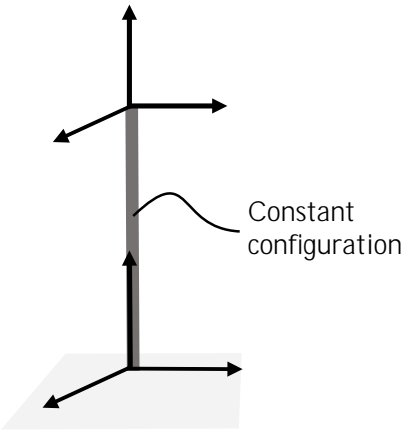
Standard Extension of PCC to 3D (kinematics)



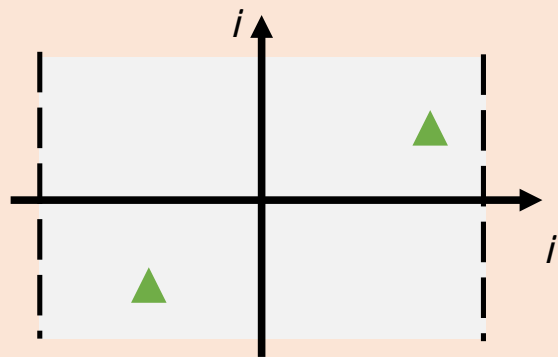
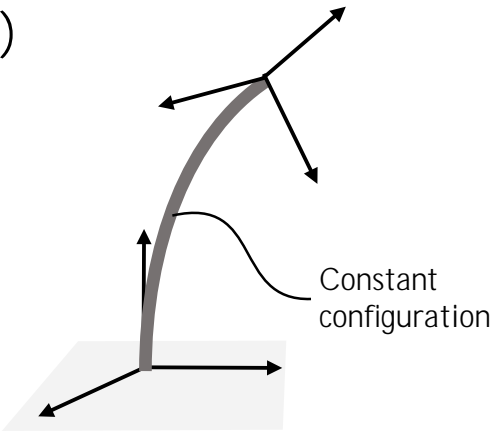
Physical configuration

parametrization

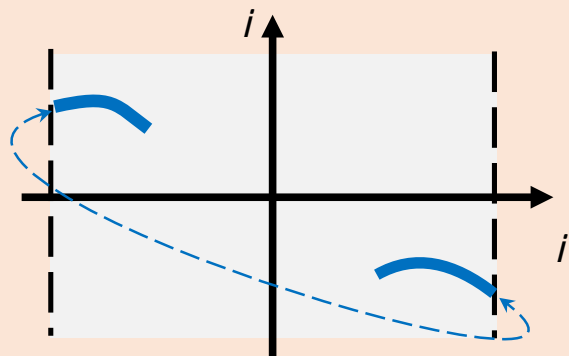
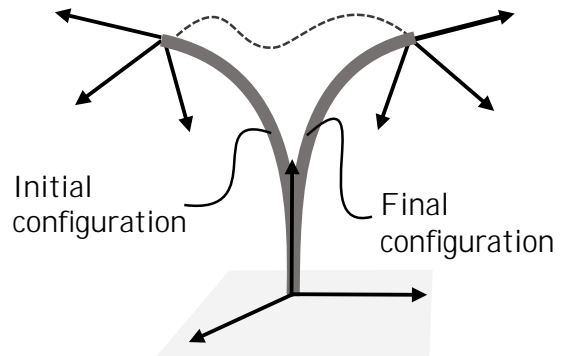
a)



b)

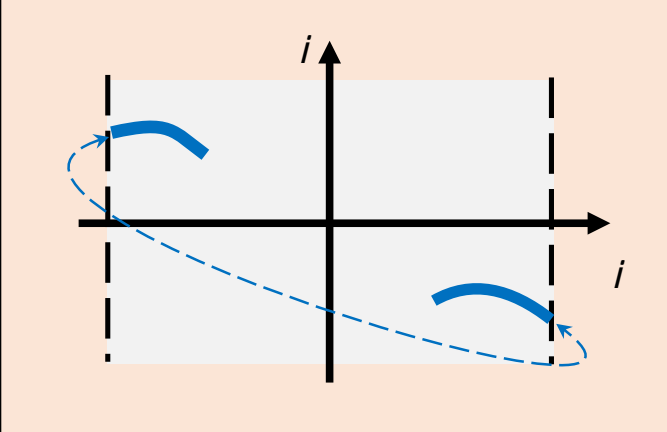
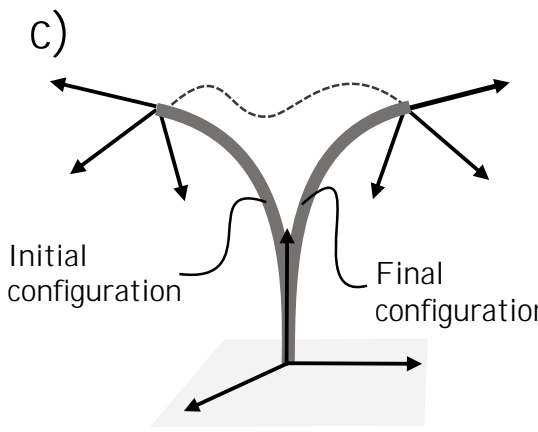
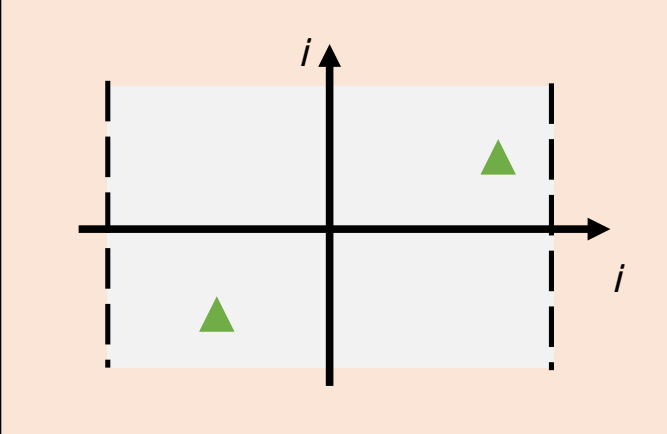
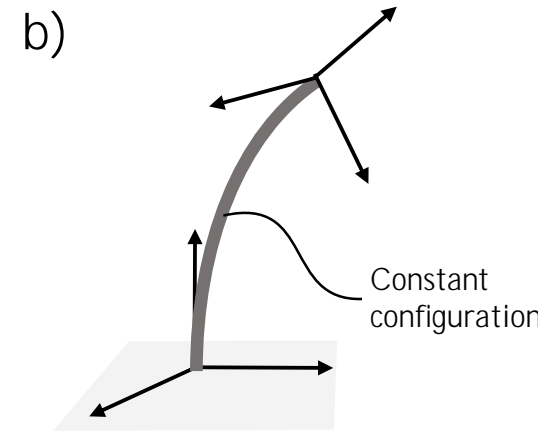
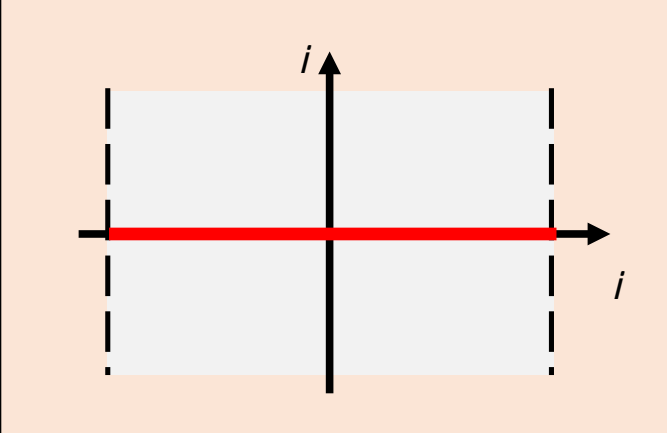
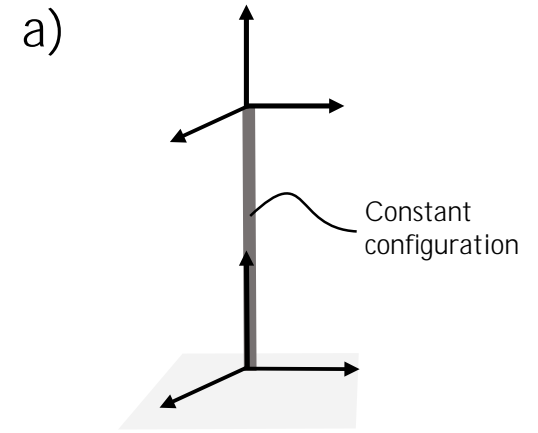


c)



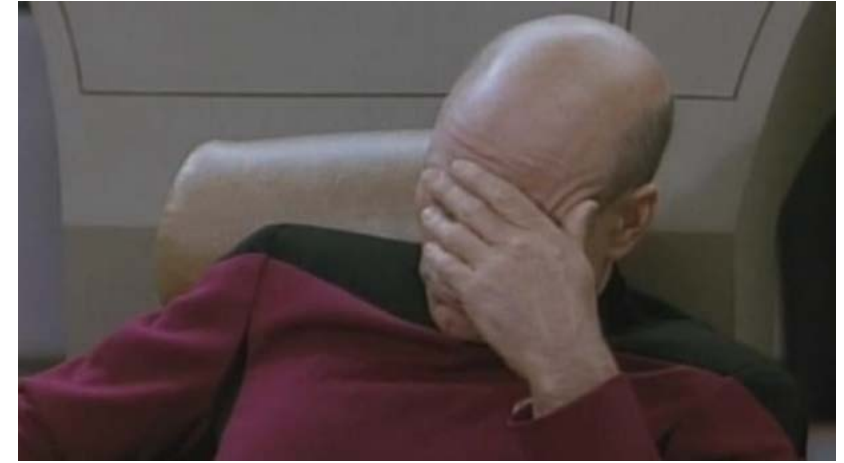
Physical configuration

parametrization



S^n Topology

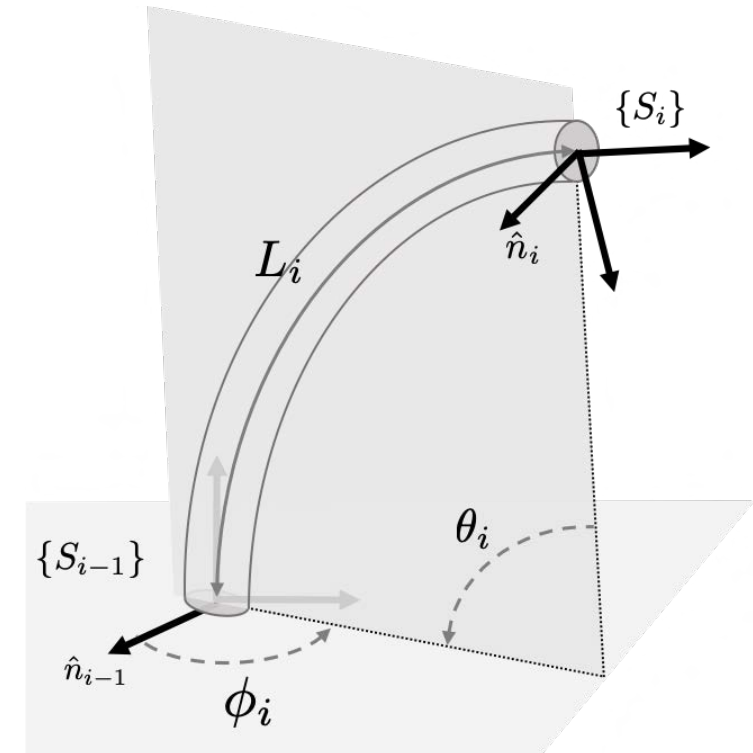
All kinds of pathological behaviors around the straight configuration



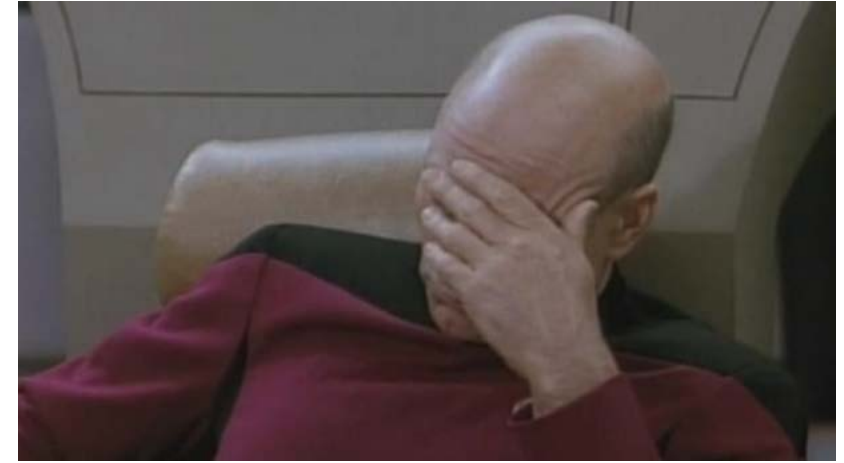
Father of all sins: singular Jacobian

$${}^x J_{\alpha,i} = \begin{bmatrix} \frac{s\phi_i (1-c\theta_i) L_i}{\theta_i} & \frac{c\phi_i L_i (1-c\theta_i - \theta_i s\theta_i)}{\theta_i^2} & \frac{c\phi_i (c\theta_i - 1)}{\theta_i} \\ \frac{c\phi_i (c\theta_i - 1) L_i}{\theta_i} & \frac{s\phi_i L_i (1-c\theta_i - \theta_i s\theta_i)}{\theta_i^2} & \frac{s\phi_i (c\theta_i - 1)}{\theta_i} \\ 0 & -\frac{L_i (s\theta_i - \theta_i c\theta_i)}{\theta_i^2} & \frac{s\theta_i}{\theta_i} \end{bmatrix}$$

$$\det({}^x J_{\alpha,i}) = -\frac{(\cos(\theta_i) - 1)^2 (\delta L_i + L_{0,i})^2}{\theta_i^3}$$



All kinds of pathological behaviors around the straight configuration



Father of all sins: singular Jacobian

$${}^x J_{\alpha,i} = \begin{bmatrix} \frac{s\phi_i (1-c\theta_i) L_i}{\theta_i} & \frac{c\phi_i L_i (1-c\theta_i - \theta_i s\theta_i)}{\theta_i^2} & \frac{c\phi_i (c\theta_i - 1)}{\theta_i} \\ \frac{c\phi_i (c\theta_i - 1) L_i}{\theta_i} & \frac{s\phi_i L_i (1-c\theta_i - \theta_i s\theta_i)}{\theta_i^2} & \frac{s\phi_i (c\theta_i - 1)}{\theta_i} \\ 0 & -\frac{L_i (s\theta_i - \theta_i c\theta_i)}{\theta_i^2} & \frac{s\theta_i}{\theta_i} \end{bmatrix}$$

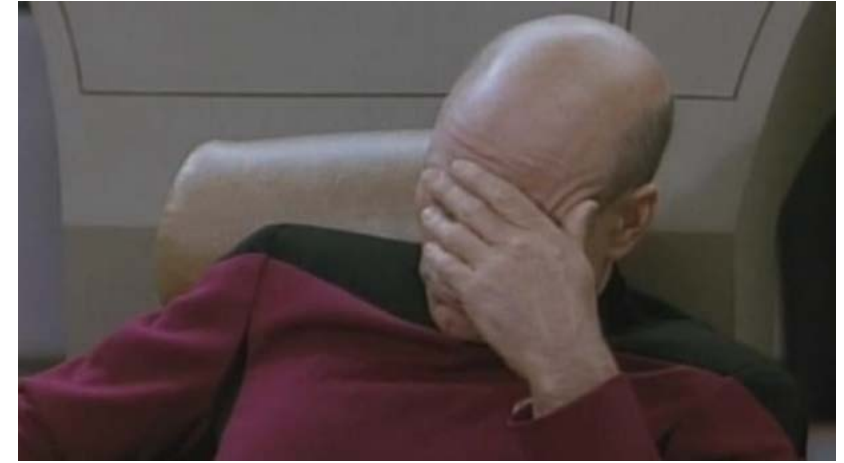
$$\det({}^x J_{\alpha,i}) = -\frac{(\cos(\theta_i) - 1)^2 (\delta L_i + L_{0,i})^2}{\theta_i^3}$$

Singular inertia matrix

$$\lim_{\theta \rightarrow 0} b_{\phi\phi}(\theta, \delta L) = 0$$

$$B_{\alpha} = \mu ({}^x J_{\alpha}^T {}^x J_{\alpha}) = \mu \begin{bmatrix} b_{\phi\phi}(\theta, \delta L) & 0 & 0 \\ 0 & * & * \\ 0 & * & * \end{bmatrix}$$

All kinds of pathological behaviors around the straight configuration



Father of all sins: singular Jacobian

$${}^x J_{\alpha,i} = \begin{bmatrix} \frac{s_{\phi_i} (1 - c_{\theta_i}) L_i}{\theta_i} & \frac{c_{\phi_i} L_i (1 - c_{\theta_i} - \theta_i s_{\theta_i})}{\theta_i^2} & \frac{c_{\phi_i} (c_{\theta_i} - 1)}{\theta_i} \\ \frac{c_{\phi_i} (c_{\theta_i} - 1) L_i}{\theta_i} & \frac{s_{\phi_i} L_i (1 - c_{\theta_i} - \theta_i s_{\theta_i})}{\theta_i^2} & \frac{s_{\phi_i} (c_{\theta_i} - 1)}{\theta_i} \\ 0 & -\frac{L_i (s_{\theta_i} - \theta_i c_{\theta_i})}{\theta_i^2} & \frac{s_{\theta_i}}{\theta_i} \end{bmatrix}$$

$$\det({}^x J_{\alpha,i}) = -\frac{(\cos(\theta_i) - 1)^2 (\delta L_i + L_{0,i})^2}{\theta_i^3}$$

Singular inertia matrix

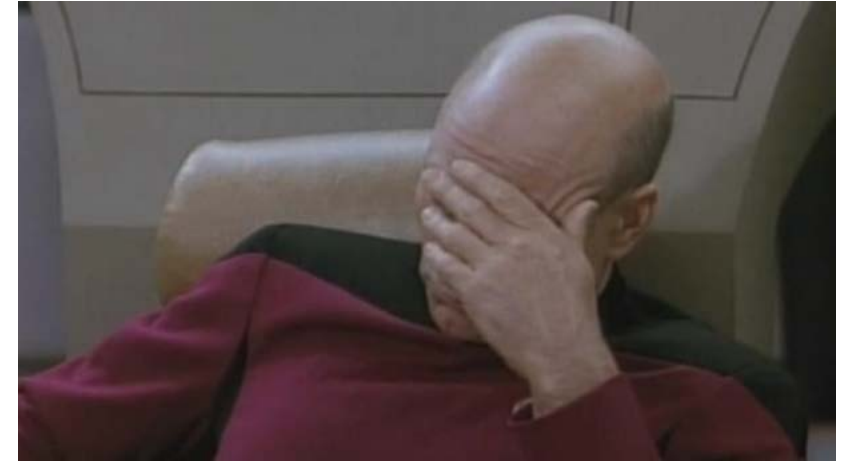
$$\lim_{\theta \rightarrow 0} b_{\phi\phi}(\theta, \delta L) = 0$$

$$B_{\alpha} = \mu ({}^x J_{\alpha}^T {}^x J_{\alpha}) = \mu \begin{bmatrix} b_{\phi\phi}(\theta, \delta L) & 0 & 0 \\ 0 & * & * \\ 0 & * & * \end{bmatrix}$$

Singular input field

$$A_{\alpha,i}(\phi_i, 0, \delta L_i) = \begin{bmatrix} 0 & 0 & 0 \\ -s_{\phi_i} & c_{\phi_i} & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

All kinds of pathological behaviors around the straight configuration



Father of all sins: singular Jacobian

$${}^x J_{\alpha,i} = \begin{bmatrix} \frac{s\phi_i (1-c\theta_i) L_i}{\theta_i} & \frac{c\phi_i L_i (1-c\theta_i - \theta_i s\theta_i)}{\theta_i^2} & \frac{c\phi_i (c\theta_i - 1)}{\theta_i} \\ \frac{c\phi_i (c\theta_i - 1) L_i}{\theta_i} & \frac{s\phi_i L_i (1-c\theta_i - \theta_i s\theta_i)}{\theta_i^2} & \frac{s\phi_i (c\theta_i - 1)}{\theta_i} \\ 0 & -\frac{L_i (s\theta_i - \theta_i c\theta_i)}{\theta_i^2} & \frac{s\theta_i}{\theta_i} \end{bmatrix}$$

$$\det({}^x J_{\alpha,i}) = -\frac{(\cos(\theta_i) - 1)^2 (\delta L_i + L_{0,i})^2}{\theta_i^3}$$

Singular inertia matrix

$$\lim_{\theta \rightarrow 0} b_{\phi\phi}(\theta, \delta L) = 0$$

$$B_{\alpha} = \mu ({}^x J_{\alpha}^T {}^x J_{\alpha}) = \mu \begin{bmatrix} b_{\phi\phi}(\theta, \delta L) & 0 & 0 \\ 0 & * & * \\ 0 & * & * \end{bmatrix}$$

Singular and non linear impedance

$$K_{\alpha,i} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \kappa_{\theta,i} & 0 \\ 0 & 0 & \kappa_{\delta L,i} \end{bmatrix}$$

$$D_{\alpha,i}(\theta_i) = \begin{bmatrix} \beta_{\theta,i} \theta_i^2 & 0 & 0 \\ 0 & \beta_{\theta,i} & 0 \\ 0 & 0 & \beta_{\delta L,i} \end{bmatrix}$$

Singular input field

$$A_{\alpha,i}(\phi_i, 0, \delta L_i) = \begin{bmatrix} 0 & 0 & 0 \\ -s\phi_i & c\phi_i & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Model Based Feedback Controller

$$\begin{aligned} \tau_A = & A^{-1}(q)(G_G(q) + C(q, \dot{q})\dot{\bar{q}} + B(q)\ddot{\bar{q}} \\ & + K\bar{q} + K_P(\bar{q} - q) + D(q)\dot{\bar{q}} + K_D(\dot{\bar{q}} - \dot{q})) \end{aligned}$$

Straight
Configuration



YOU SHALL NOT PASS!

Side View

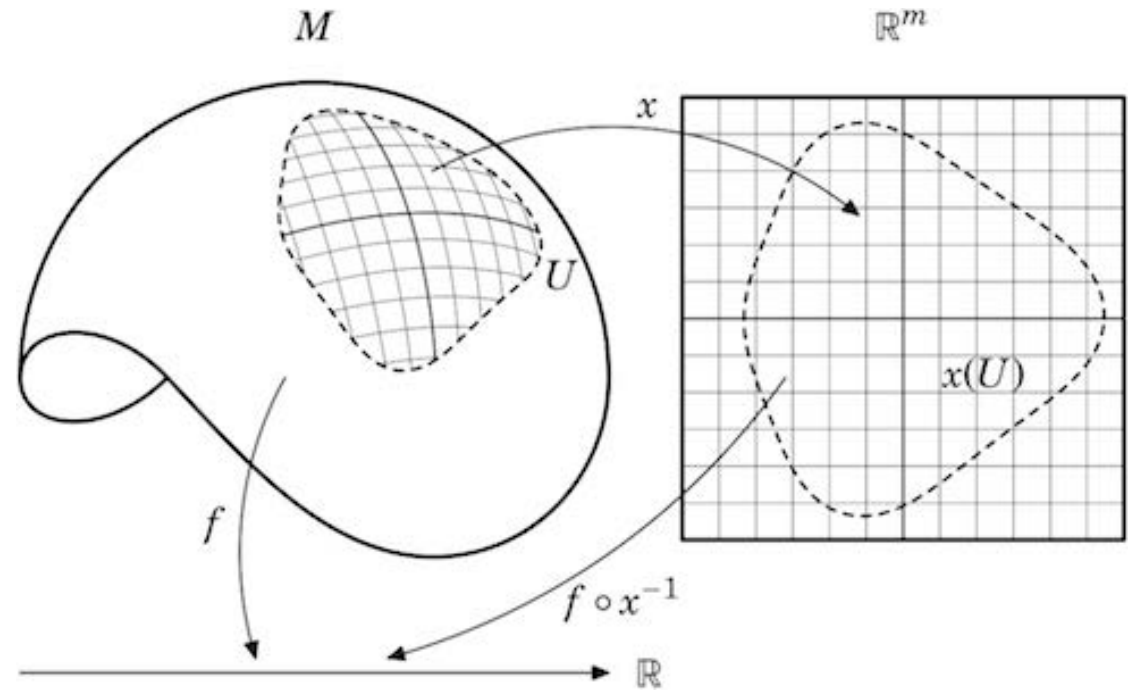


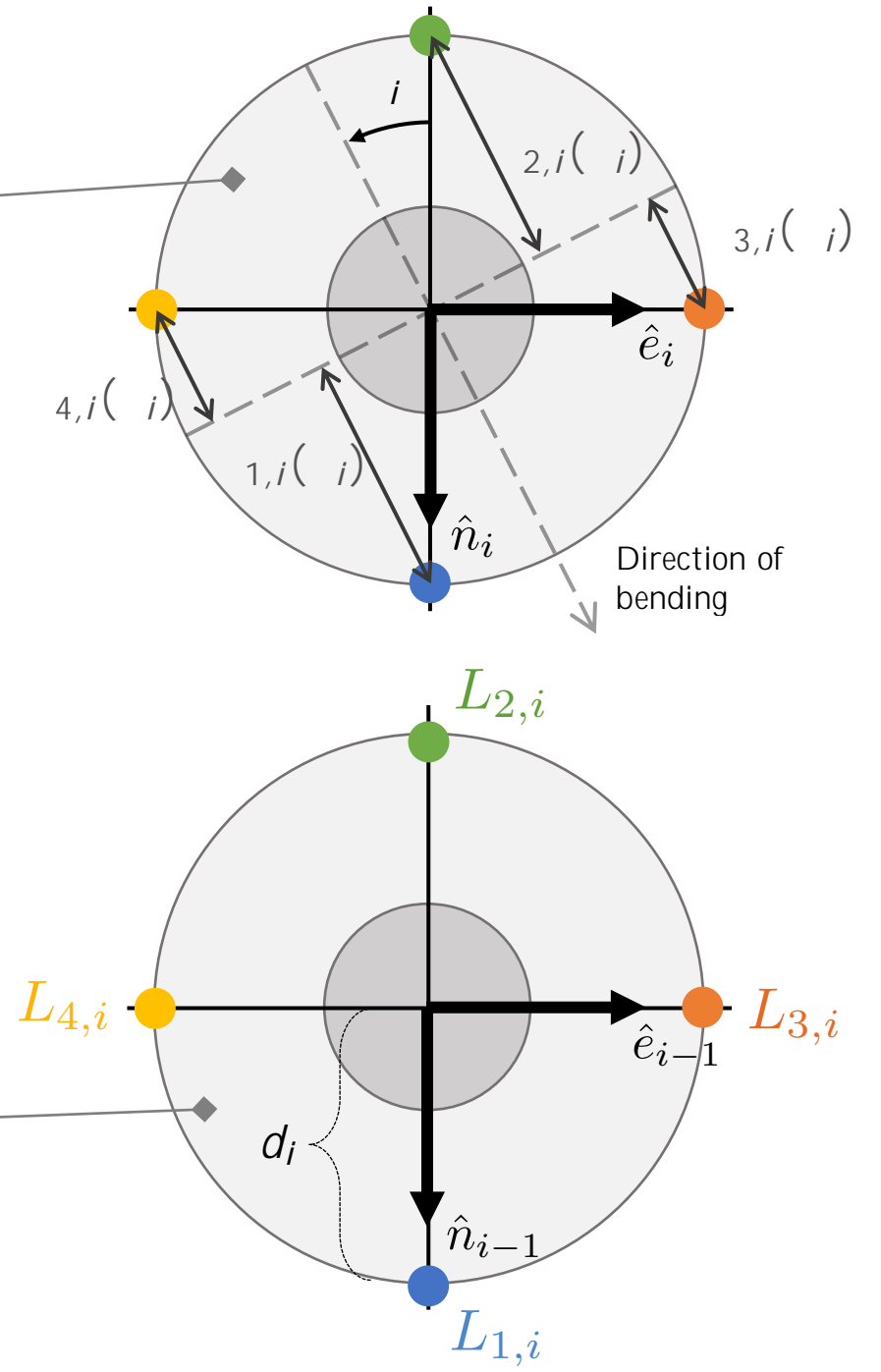
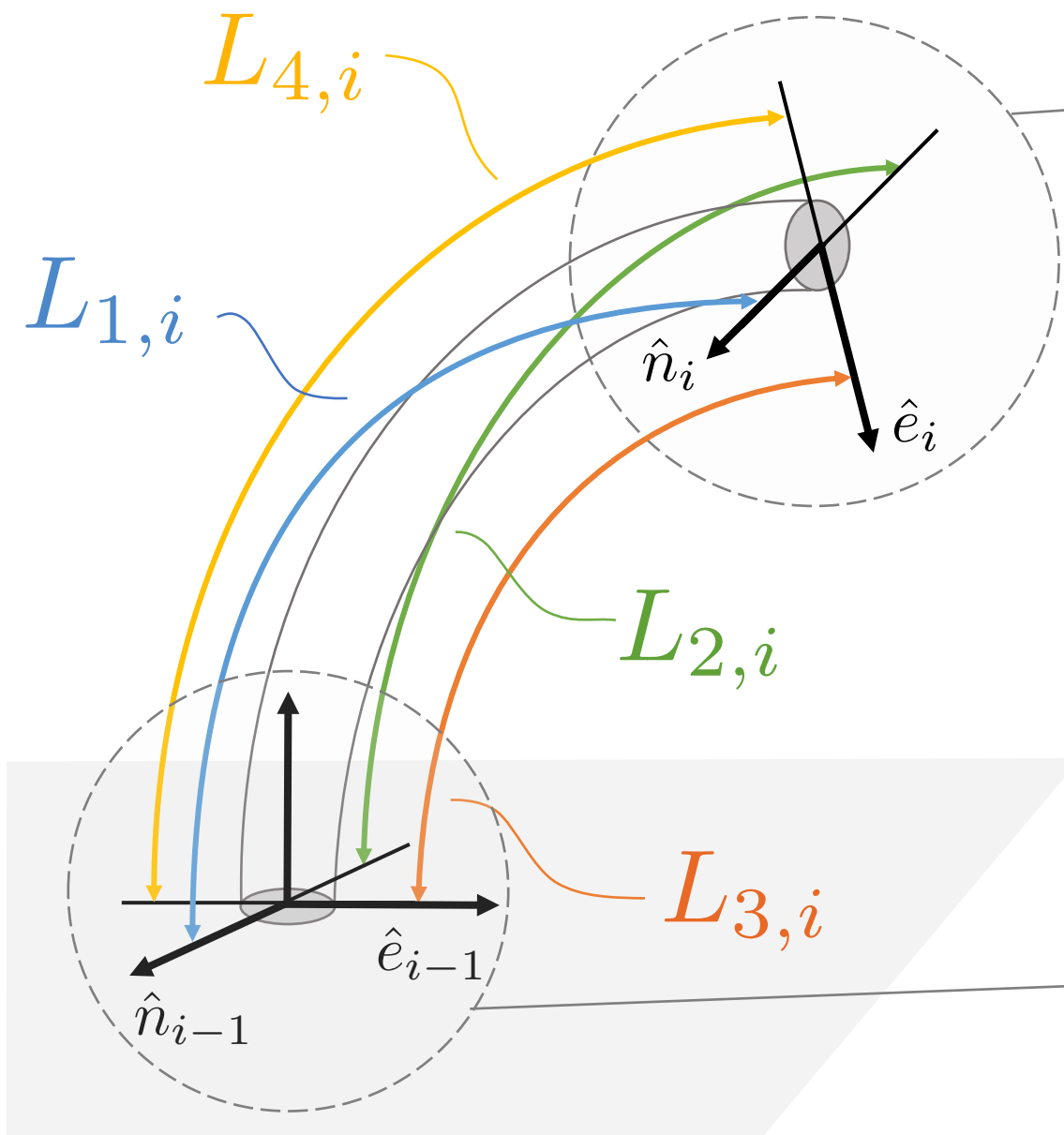
1x

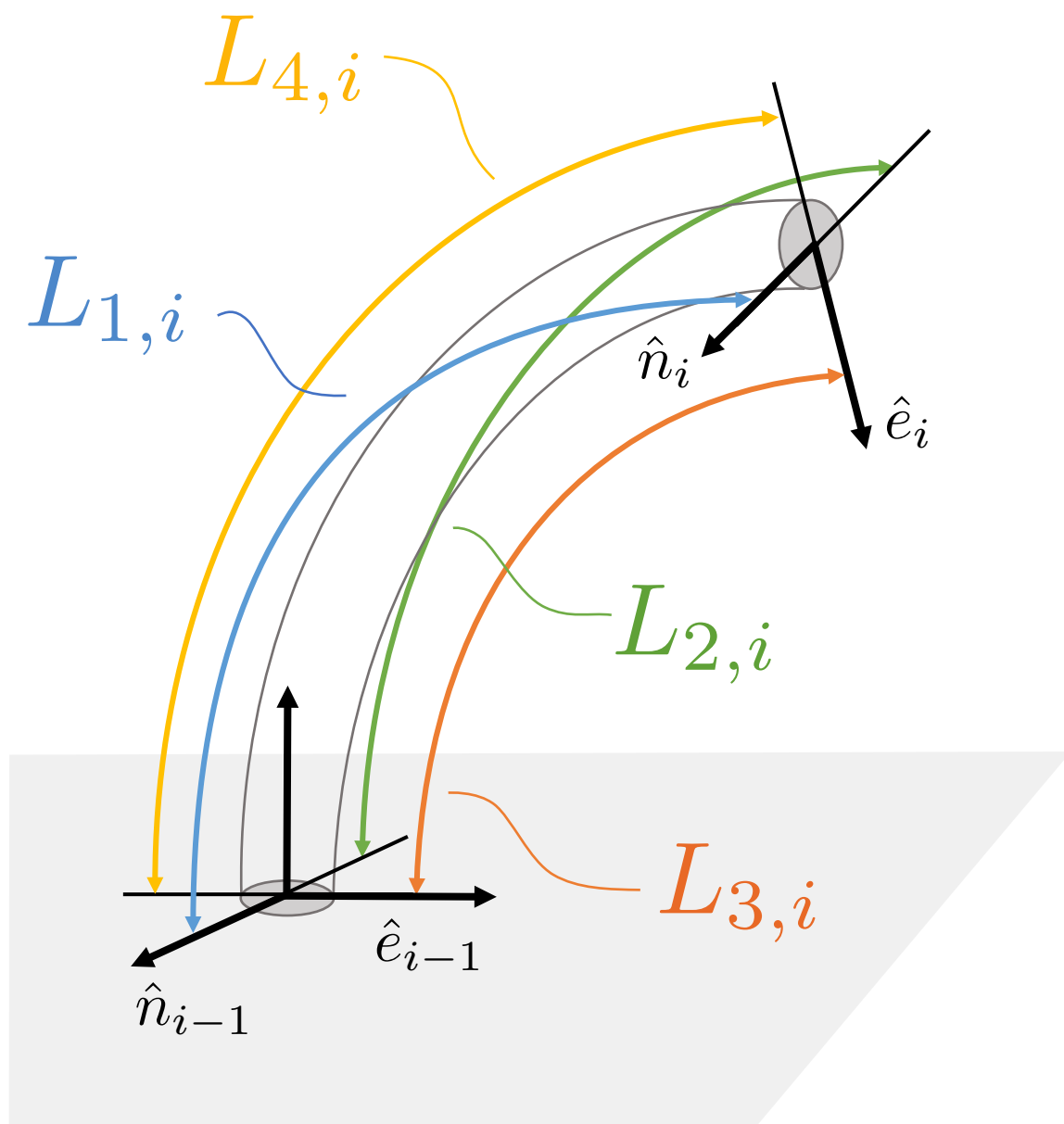


YOU SHALL NOT PASS!

The configuration manifold
is a cup, not a sphere

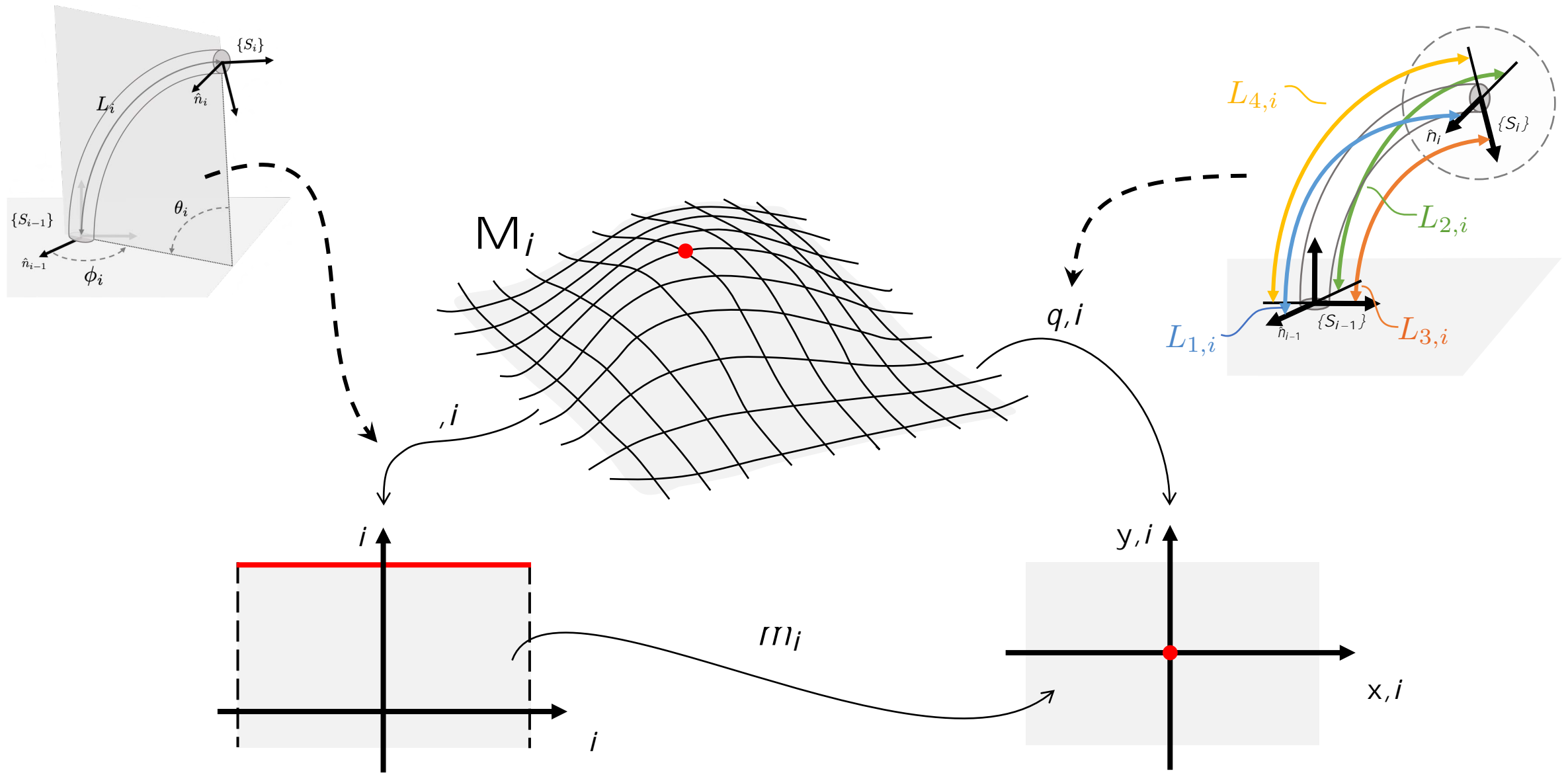






$$\Delta_{x,i} = \frac{L_{2,i} - L_{1,i}}{2}$$

$$\Delta_{y,i} = \frac{L_{4,i} - L_{3,i}}{2}$$



Full rank
Jacobian!!!

$$\det({}^x J_q) = \frac{\left(\cos \left(\sqrt{\frac{\Delta_{x,i}^2 + \Delta_{y,i}^2}{d_i}} \right) - 1 \right)^2 (\delta L_i + L_{0,i})^2}{(\Delta_{x,i}^2 + \Delta_{y,i}^2 / d_i^2)^2} \left(\frac{\delta L_i + L_{0,i}}{2} \right)^2$$

Full rank and linear impedance

$${}^\alpha J_{q,i}^T(q) K_{\alpha,i} m_i(q_i) = \begin{bmatrix} \kappa_{\theta,i} & 0 & 0 \\ 0 & \kappa_{\theta,i} & 0 \\ 0 & 0 & \kappa_{\delta L,i} \end{bmatrix} \begin{bmatrix} \Delta_{x,i} \\ \Delta_{y,i} \\ \delta L_i \end{bmatrix} \doteq K_i q$$

$$D_i \doteq {}^\alpha J_{q,i}^T(q) D_{\alpha,i}(m_i(q_i)) {}^\alpha J_{q,i}(q_i) = \begin{bmatrix} \beta_{\theta,i} & 0 & 0 \\ 0 & \beta_{\theta,i} & 0 \\ 0 & 0 & \beta_{\delta L,i} \end{bmatrix}$$

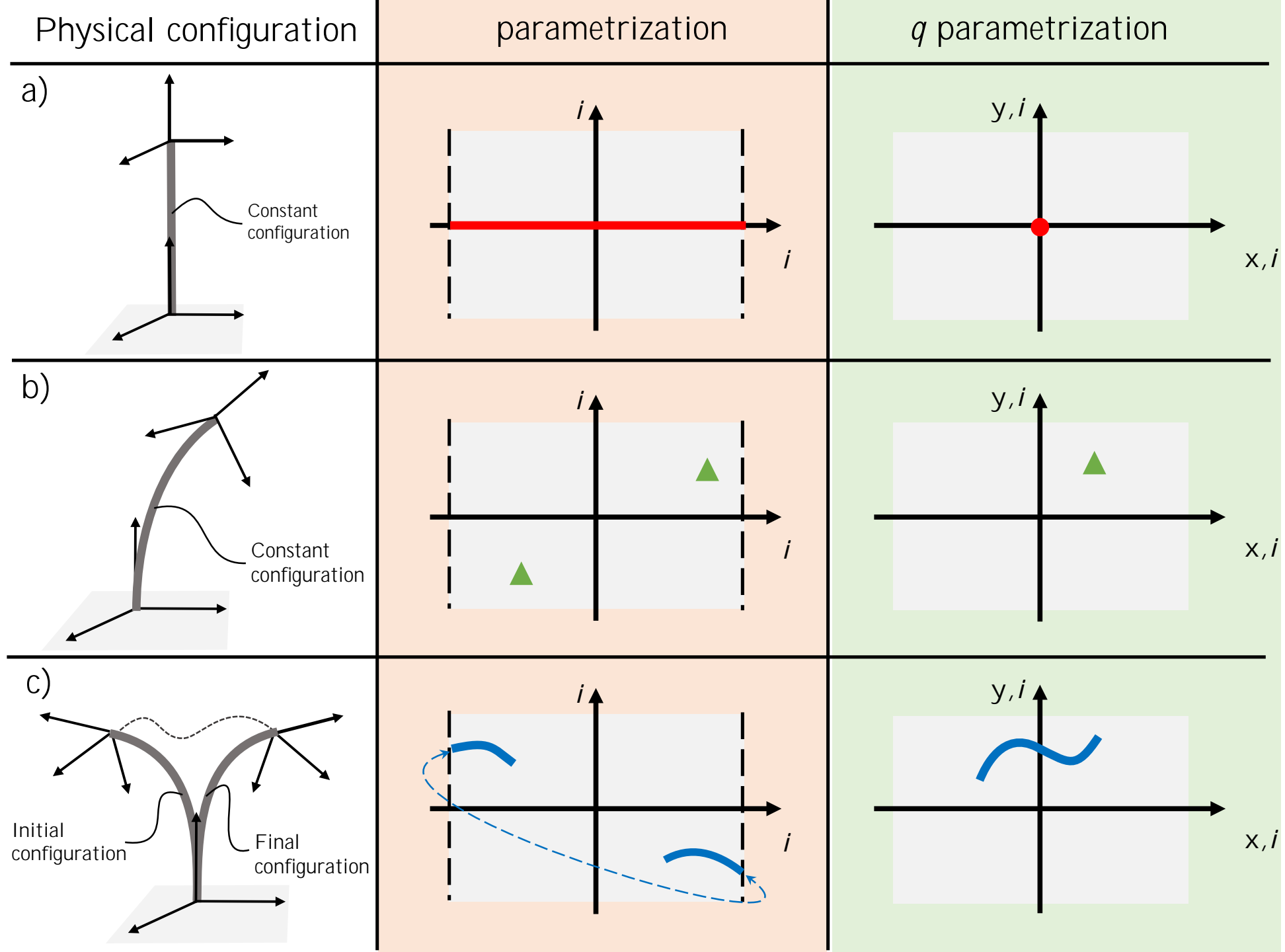
YES!!!

Full rank inertia matrix

$$\lim_{\substack{\Delta_x \rightarrow 0 \\ \Delta_y \rightarrow 0}} B(\Delta_x, \Delta_y, \delta L) = \mu \begin{bmatrix} \frac{(\delta L + L_0)^2}{4} & 0 & 0 \\ 0 & \frac{(\delta L + L_0)^2}{4} & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

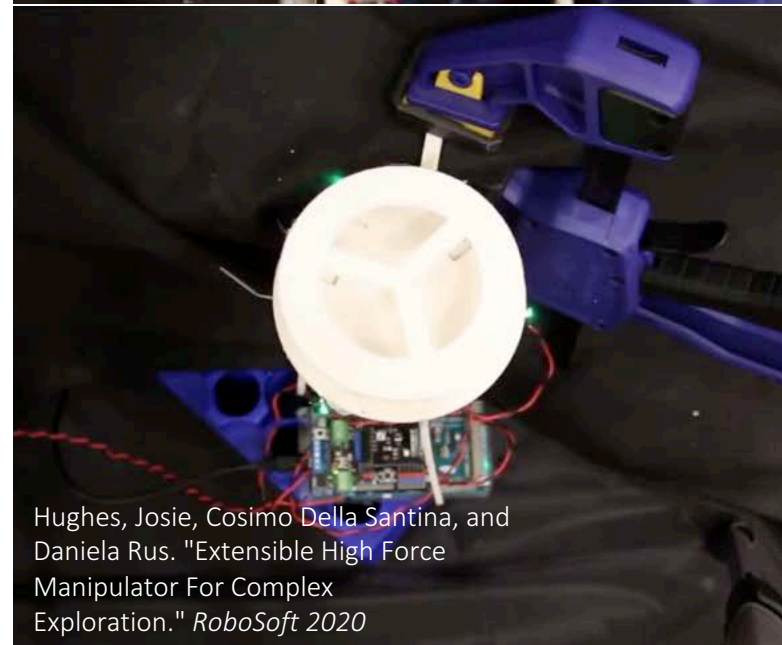
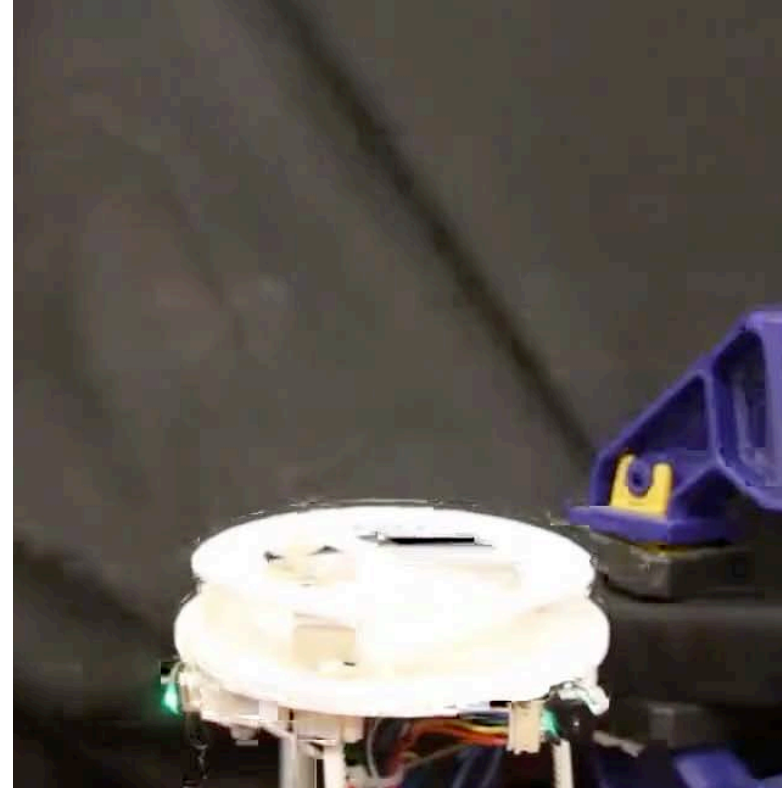
Full rank input field

$$A(q) = \begin{bmatrix} \frac{\Delta_{x,i} \Delta_{y,i} D_i}{\Delta_i^3} & \frac{-\Delta_{x,i}^2 \Delta_i - \Delta_{y,i}^2 \sin(\Delta_i)}{\Delta_i^3} & \frac{\Delta_{x,i} D_i L_i}{\Delta_i^3} \\ \frac{\Delta_{y,i}^2 \Delta_i + \Delta_{x,i}^2 \sin(\Delta_i)}{\Delta_i^3} & \frac{-\Delta_{x,i} \Delta_{y,i} D_i}{\Delta_i^3} & \frac{\Delta_{y,i} D_i L_i}{\Delta_i^3} \\ 0 & 0 & \frac{\sin(\Delta_i)}{\Delta_i} \end{bmatrix}$$

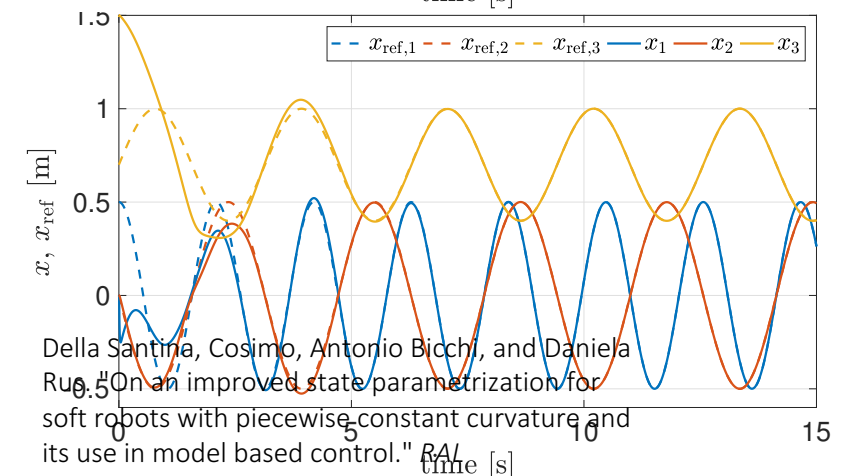
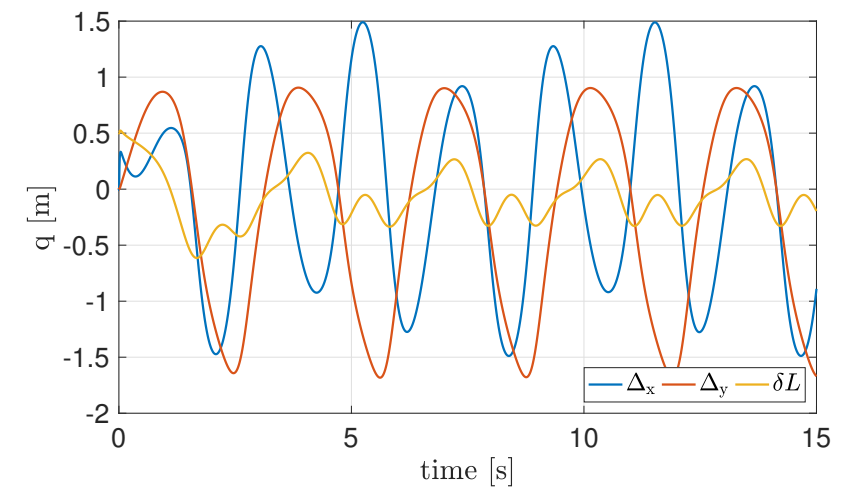
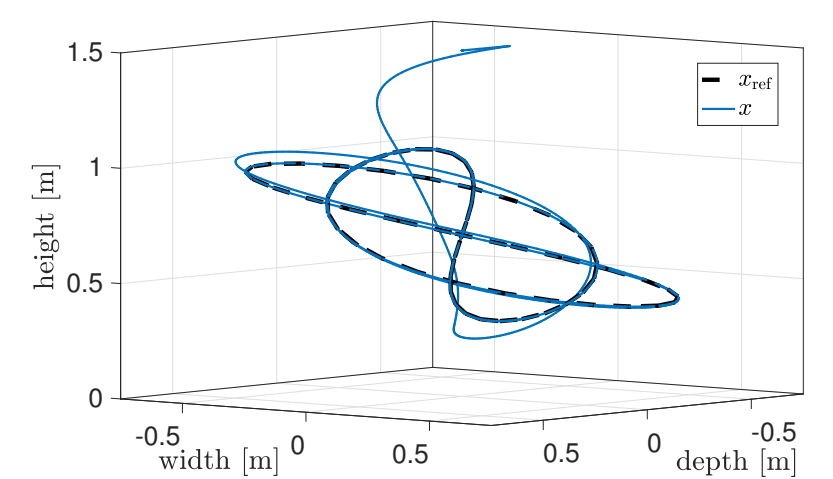




Li S., [...], Della Santina C., et al. "Dynamic control of soft robots with internal constraints in the presence of obstacles." *Submitted to SoRo*



Hughes, Josie, Cosimo Della Santina, and Daniela Rus. "Extensible High Force Manipulator For Complex Exploration." *RoboSoft 2020*



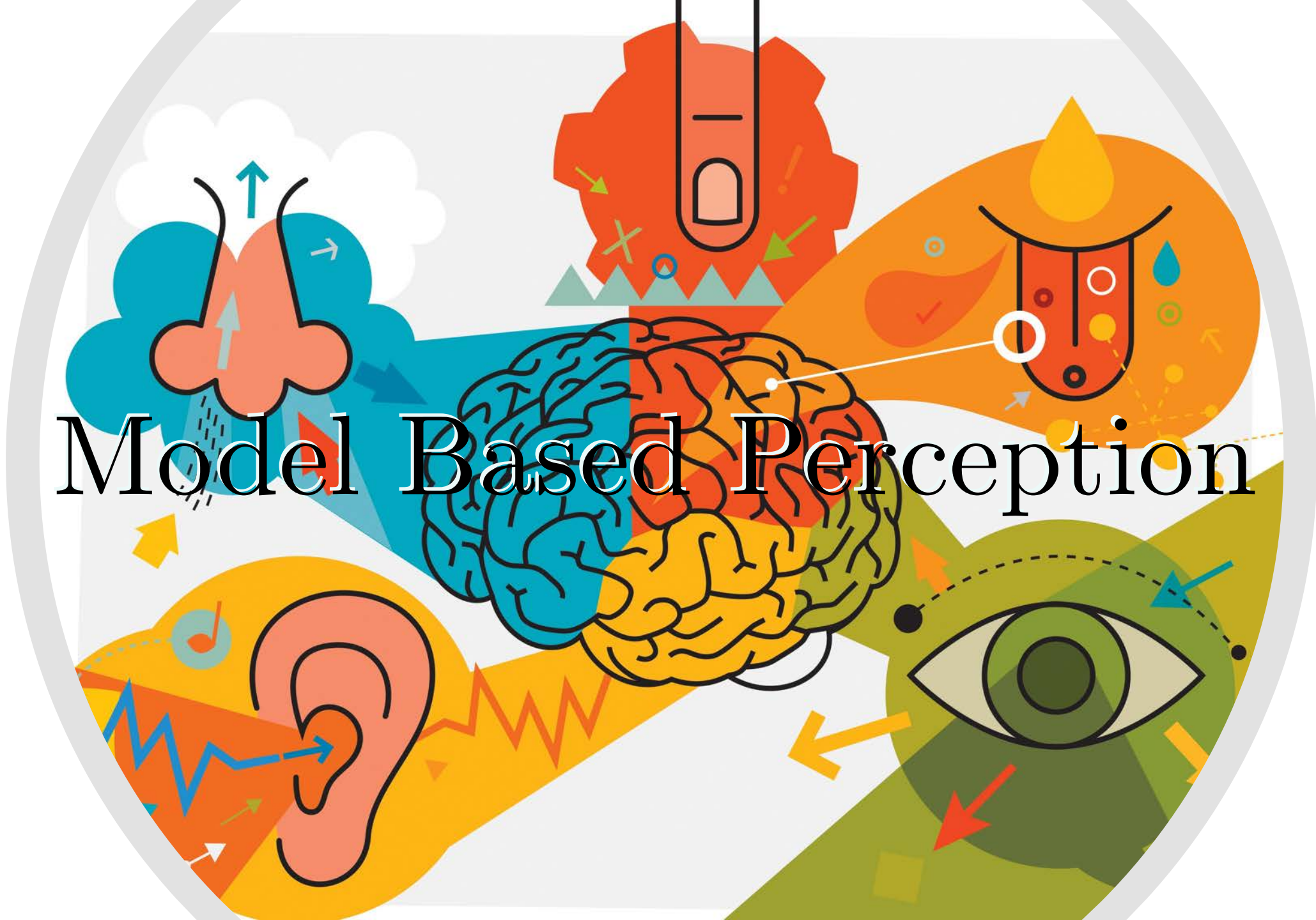
Della Santina, Cosimo, Antonio Bicchì, and Daniela Rus. "On an improved state parametrization for soft robots with piecewise constant curvature and its use in model based control." *RAI*

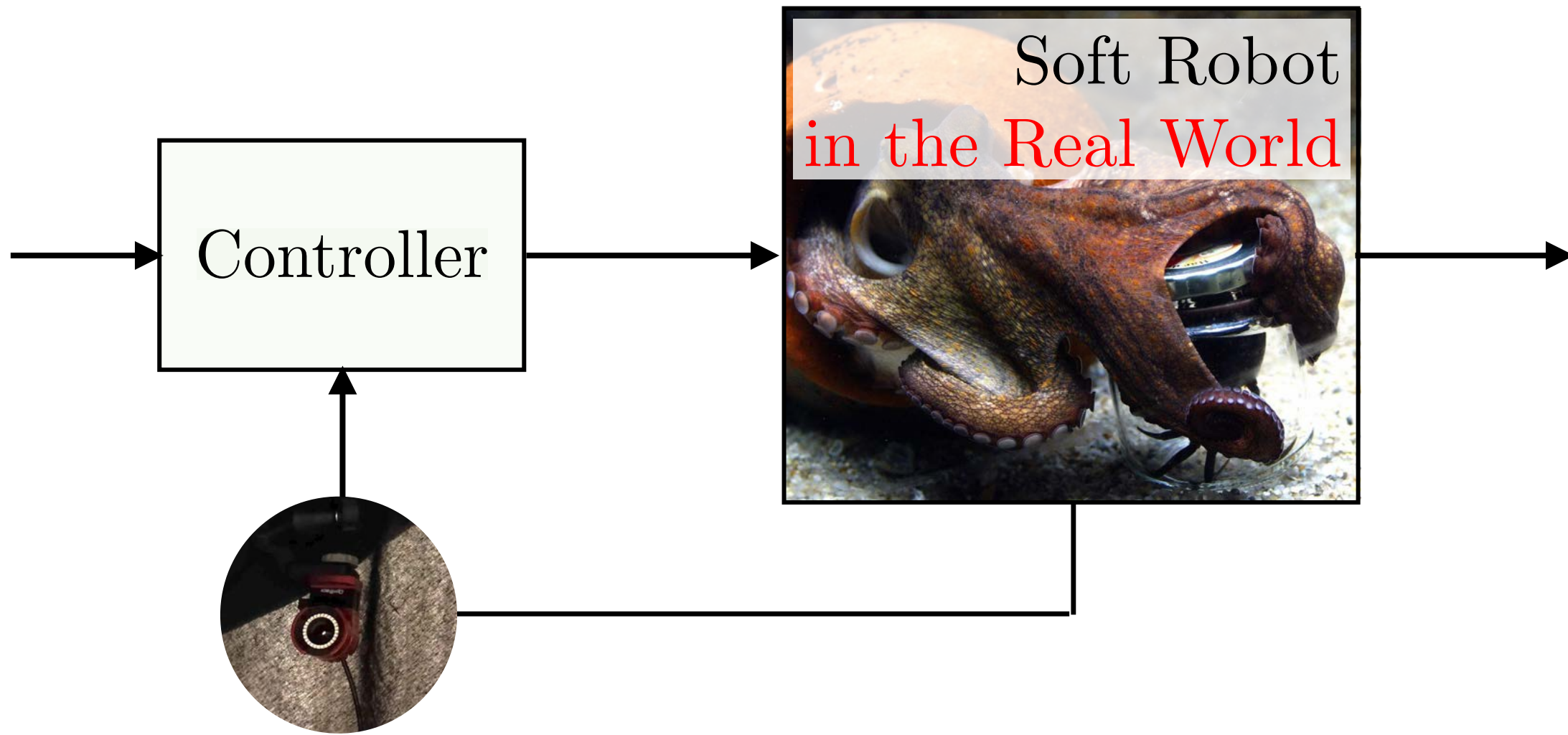
. . . and large scale soft locomotion!

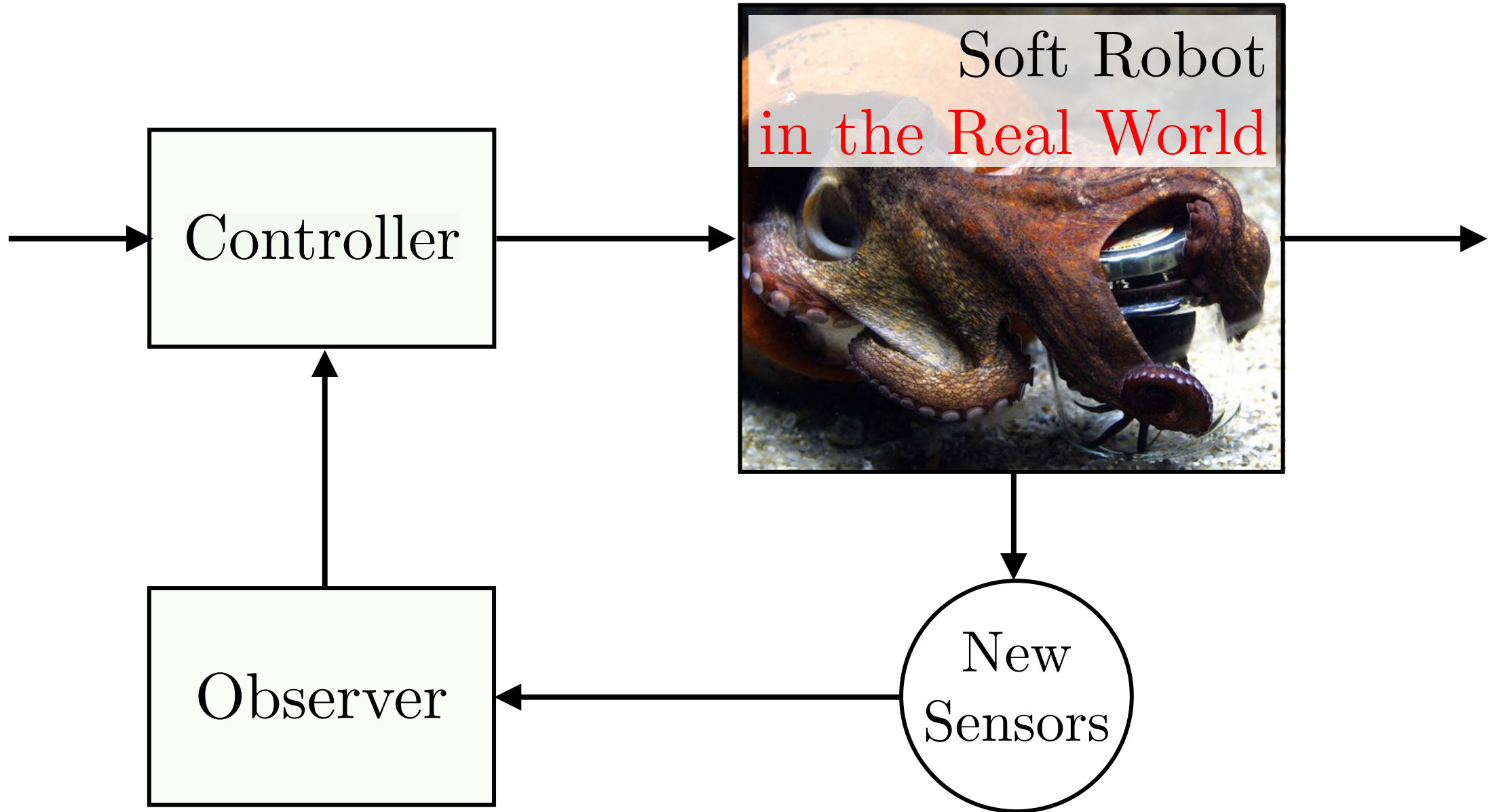


20x

Model Based Perception

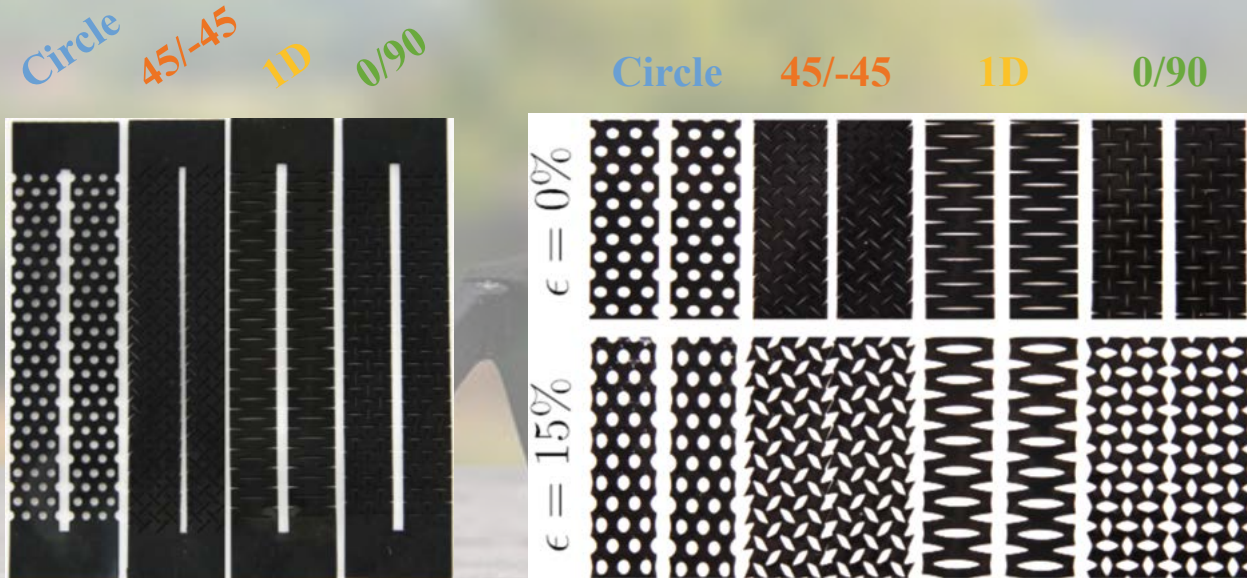






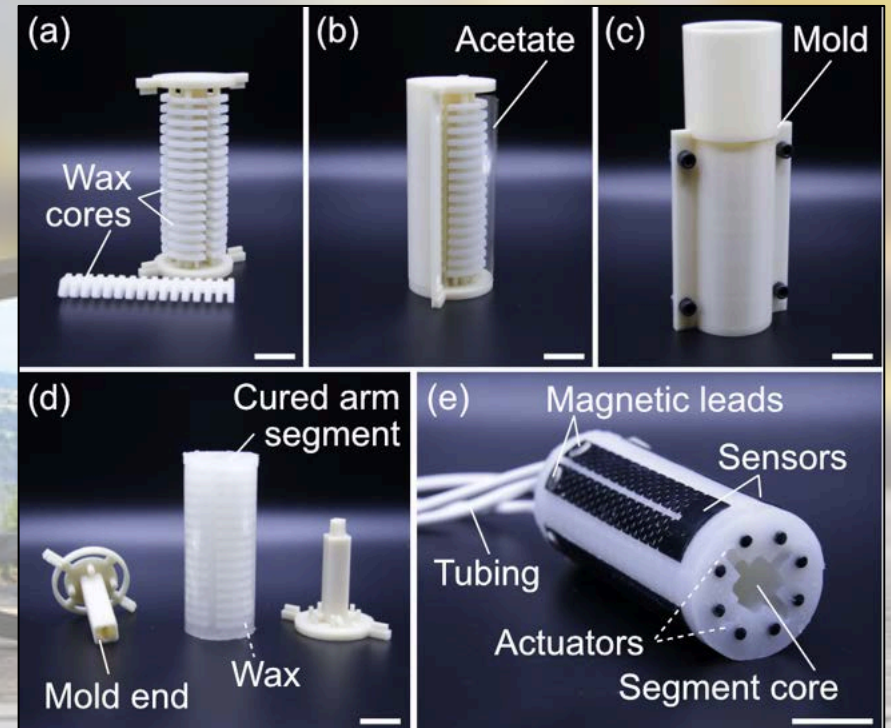
Kirigami enables a simple, rapid approach for sensorizing soft robots

Sensor design and fabrication



Electrically conductive silicone (Silux):
Shore A hardness 65 ± 5 , volume resistivity $\sim 5 \Omega\text{-cm}$

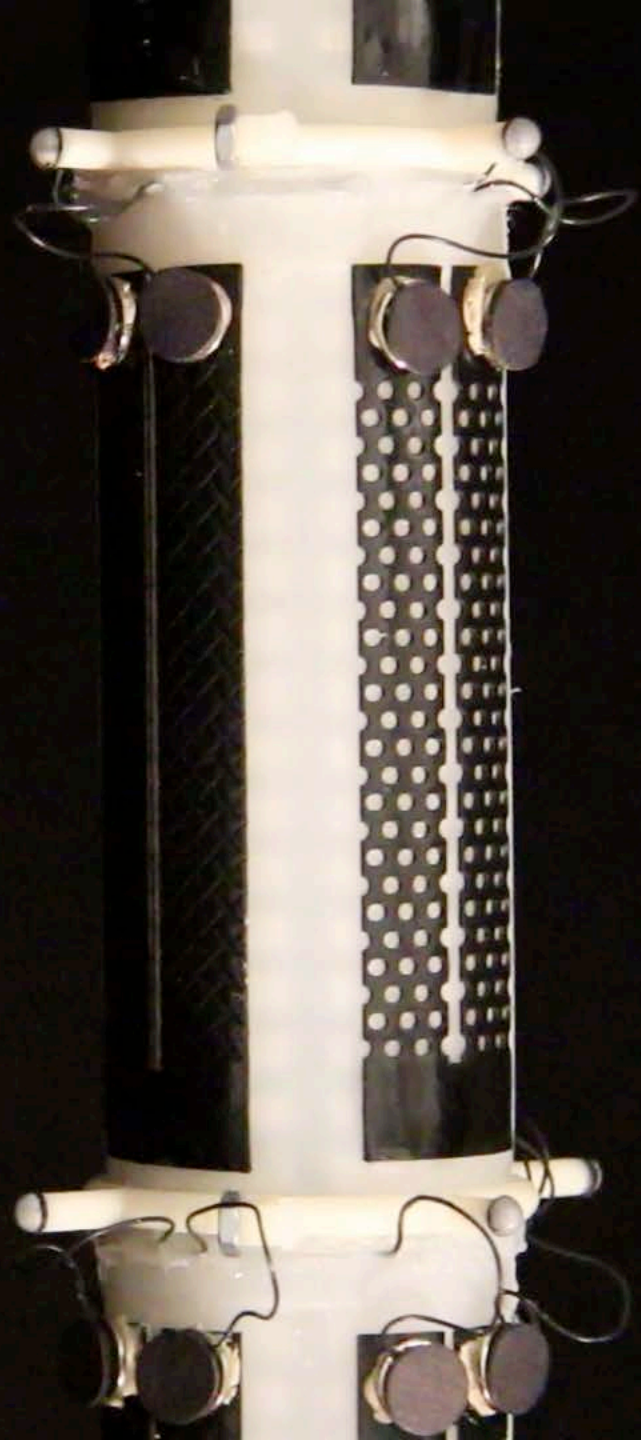
Arm fabrication via lost-wax casting

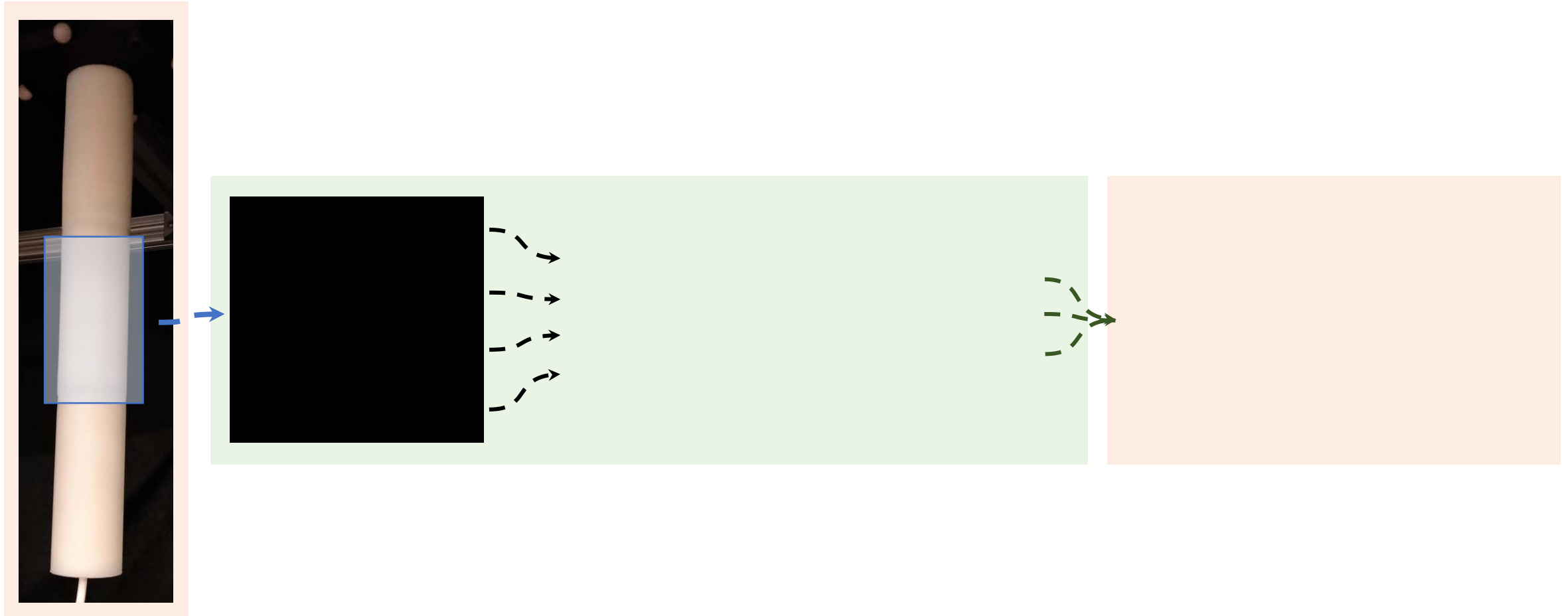


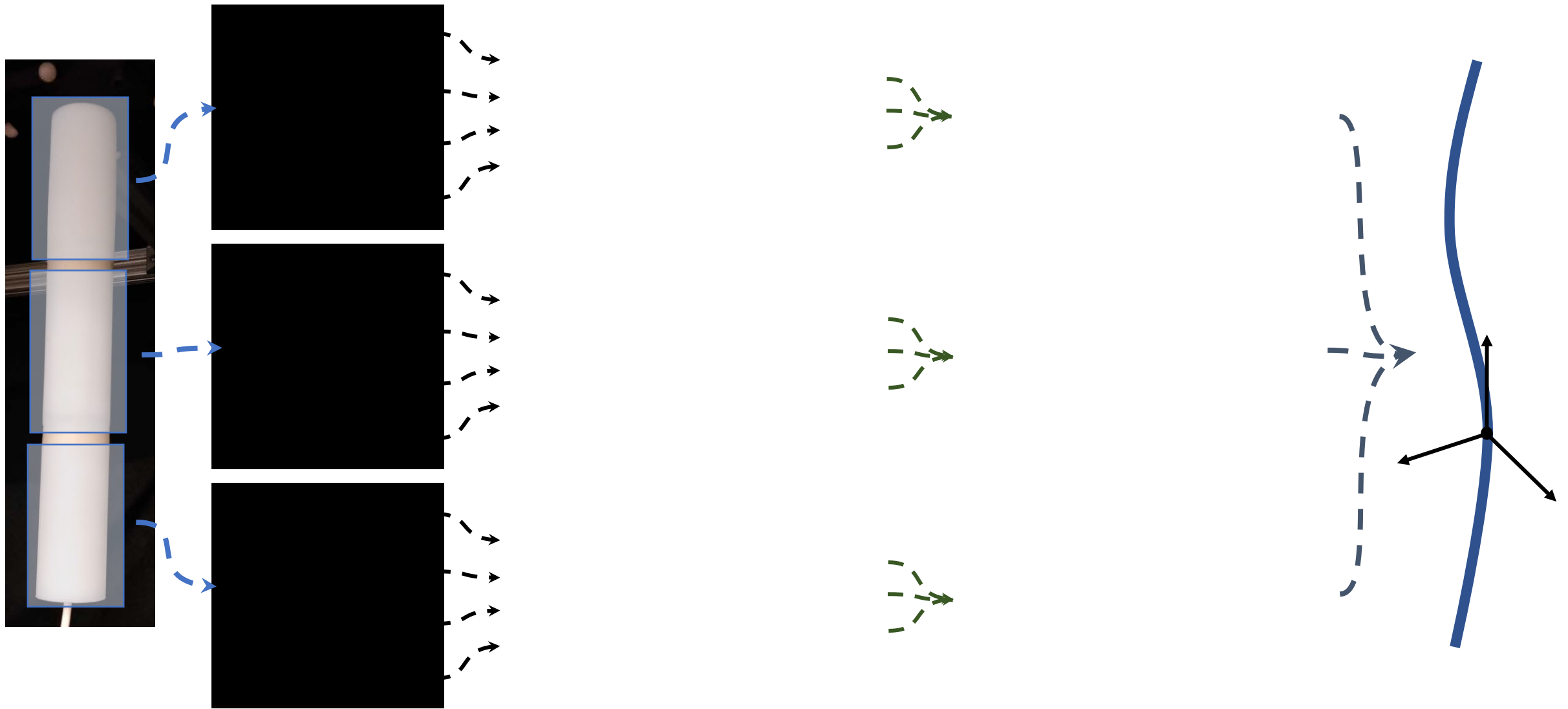
(Hypothesis: Sensor response dependent on cut pattern)

No materials handling or formulation required: sensors are laser cut and done







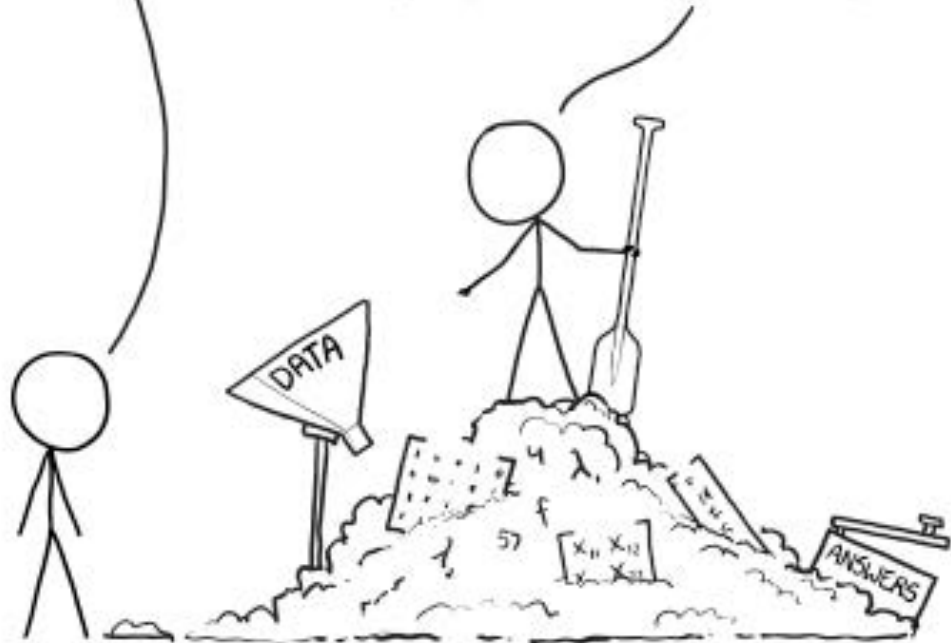


THIS IS YOUR MACHINE LEARNING SYSTEM?

YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.

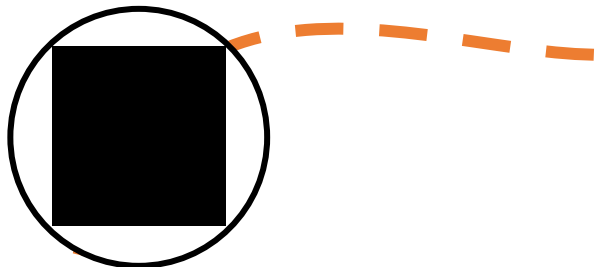
WHAT IF THE ANSWERS ARE WRONG?

JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.



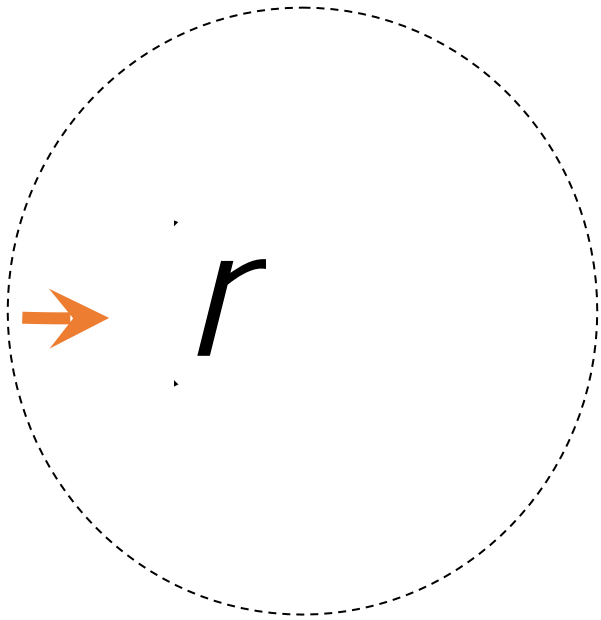
Dataset

Random
Motions

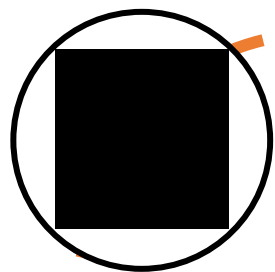


Raw Potential
Differences

\mathbb{R}^{4n}

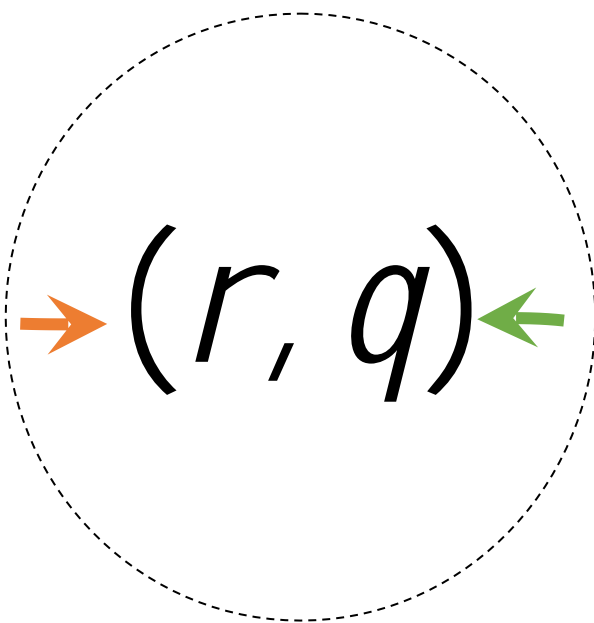


Random
Motions



Raw Potential
Differences

R^{4n}

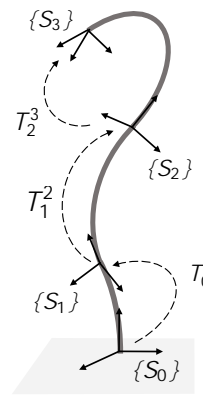


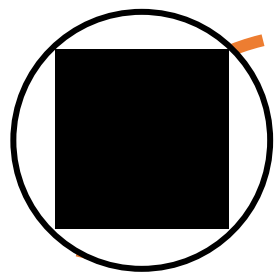
R^{3n}

Exteroceptive
Data



$SE(3) \times$
 $\dots \times$
 $SE(3)$

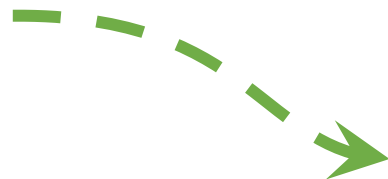




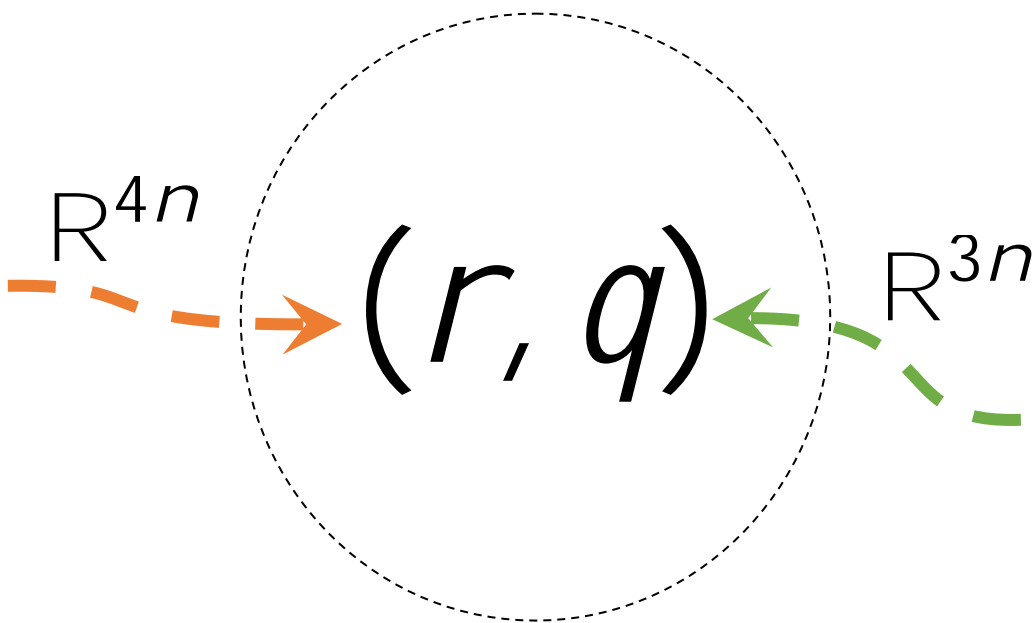
Random
Motions



Raw Potential
Differences

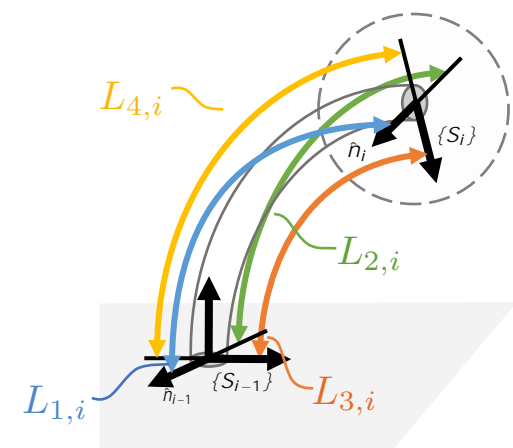
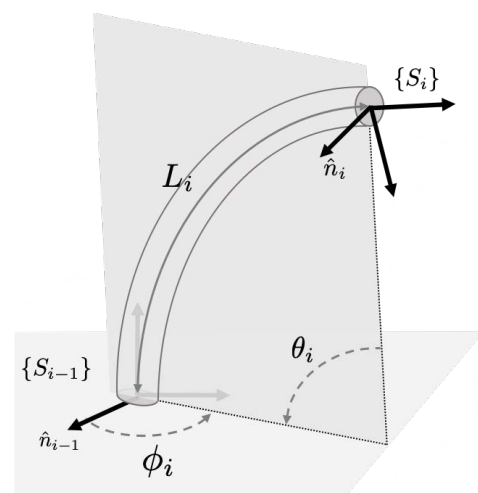
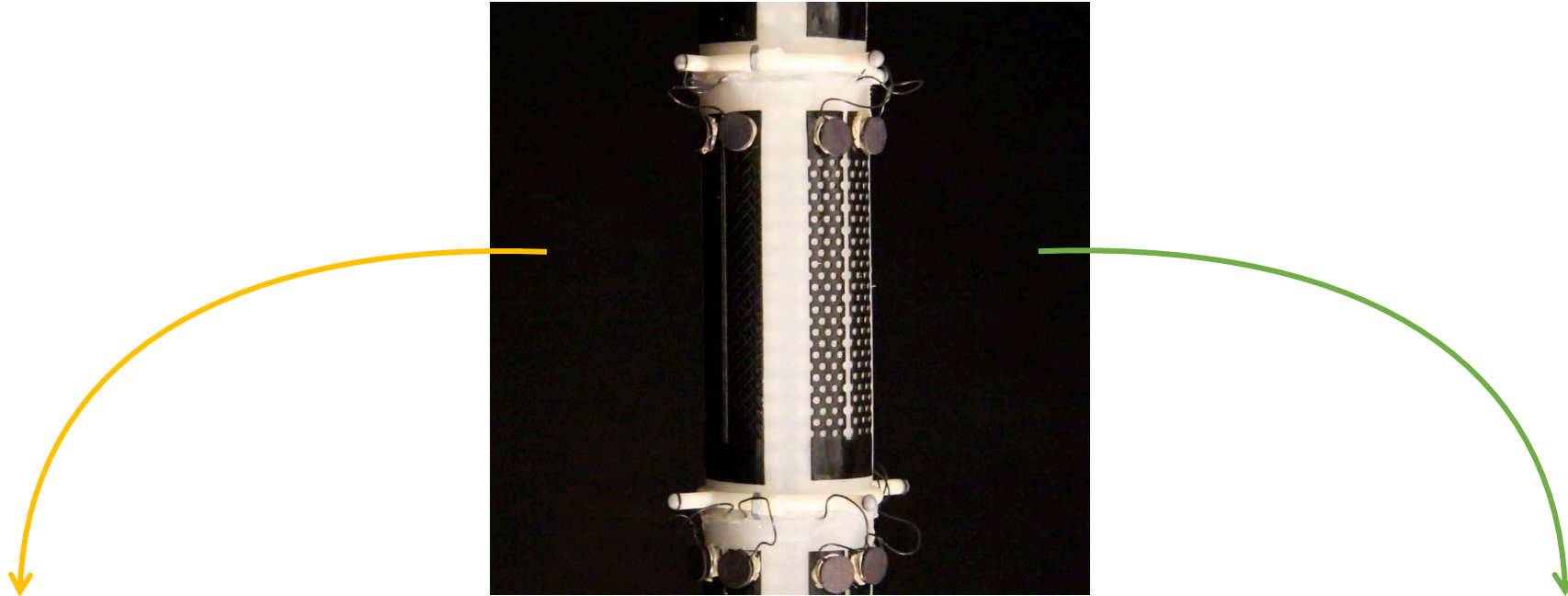


Exteroceptive
Data



$SE(3) \times$
 $\dots \times$
 $SE(3)$

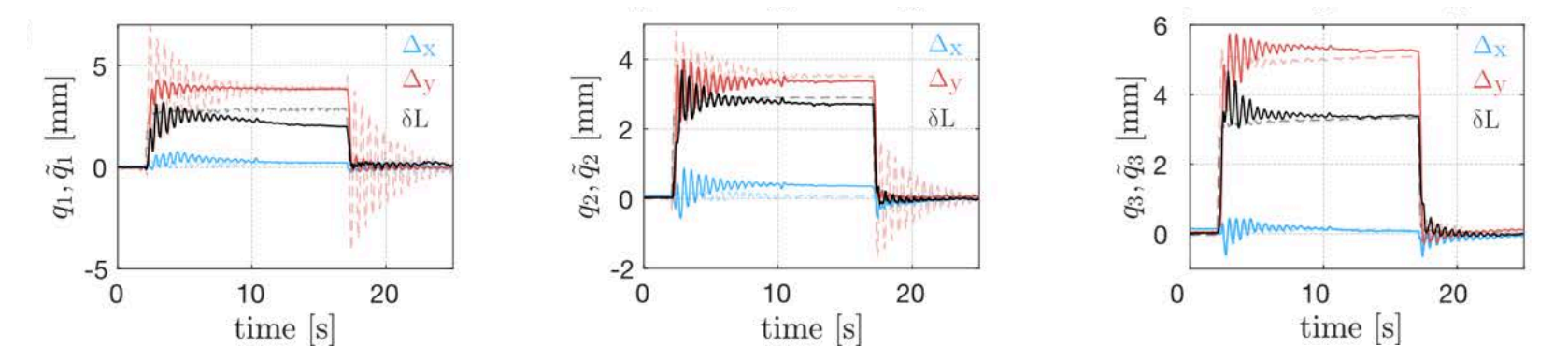
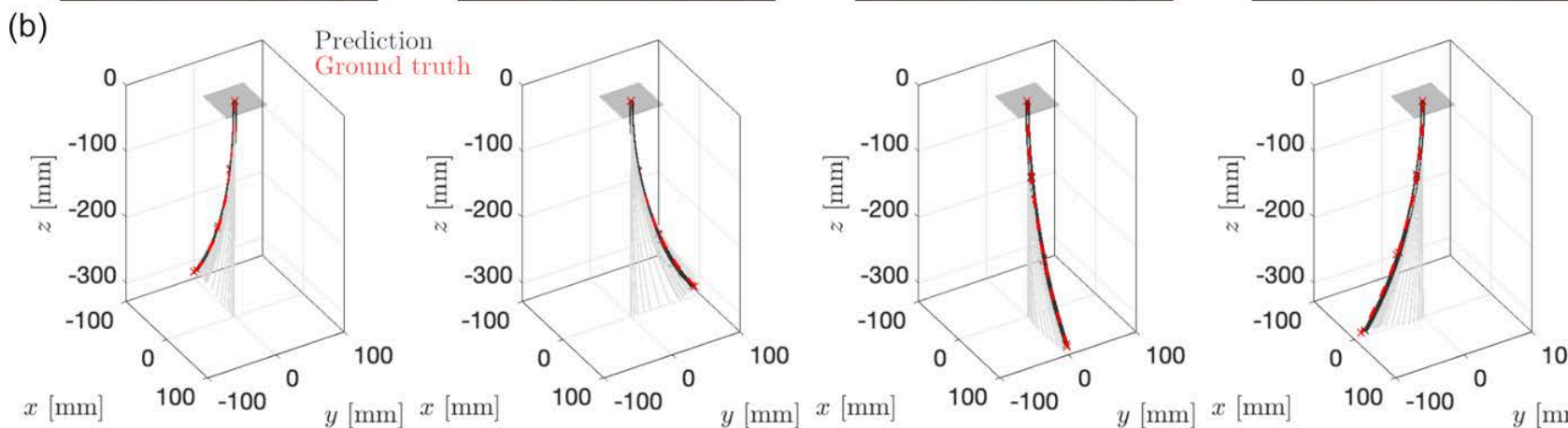
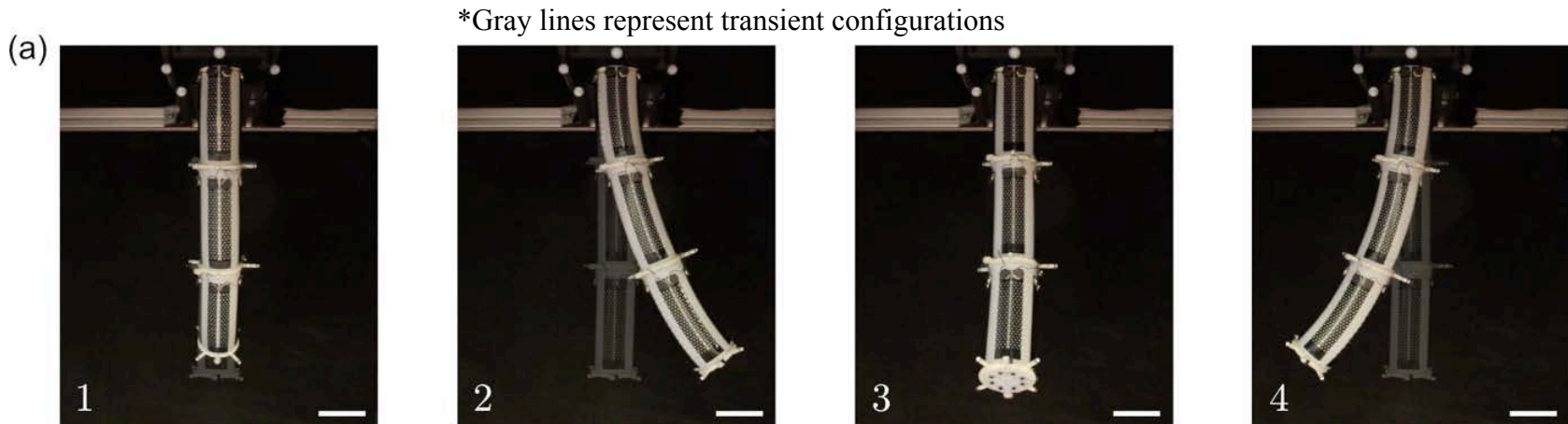
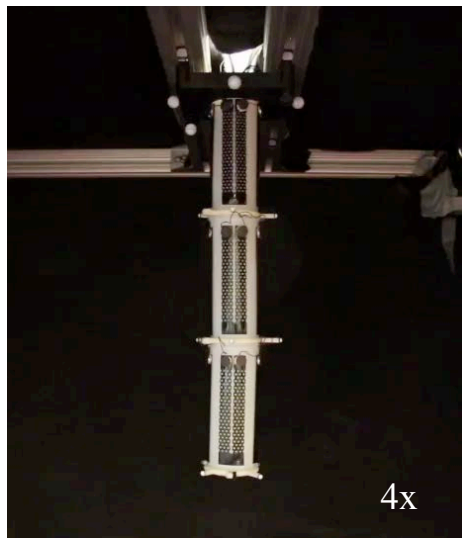




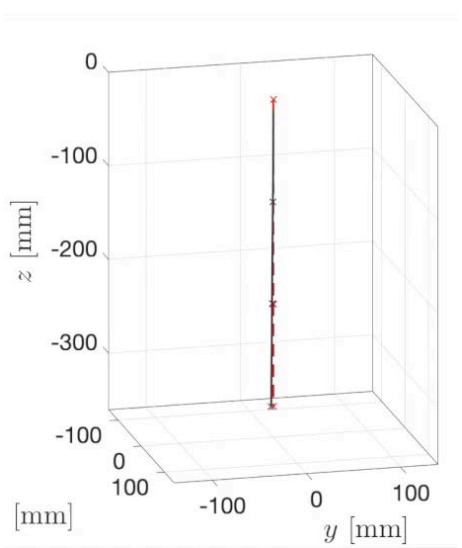


Training



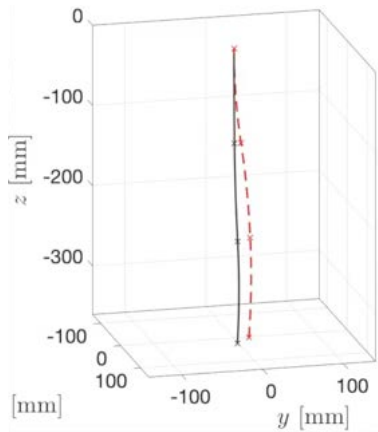
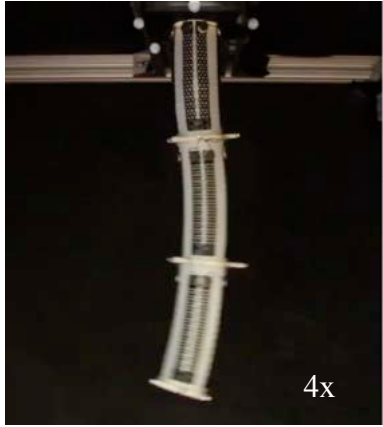


\tilde{q}_i = prediction; q_i = ground truth

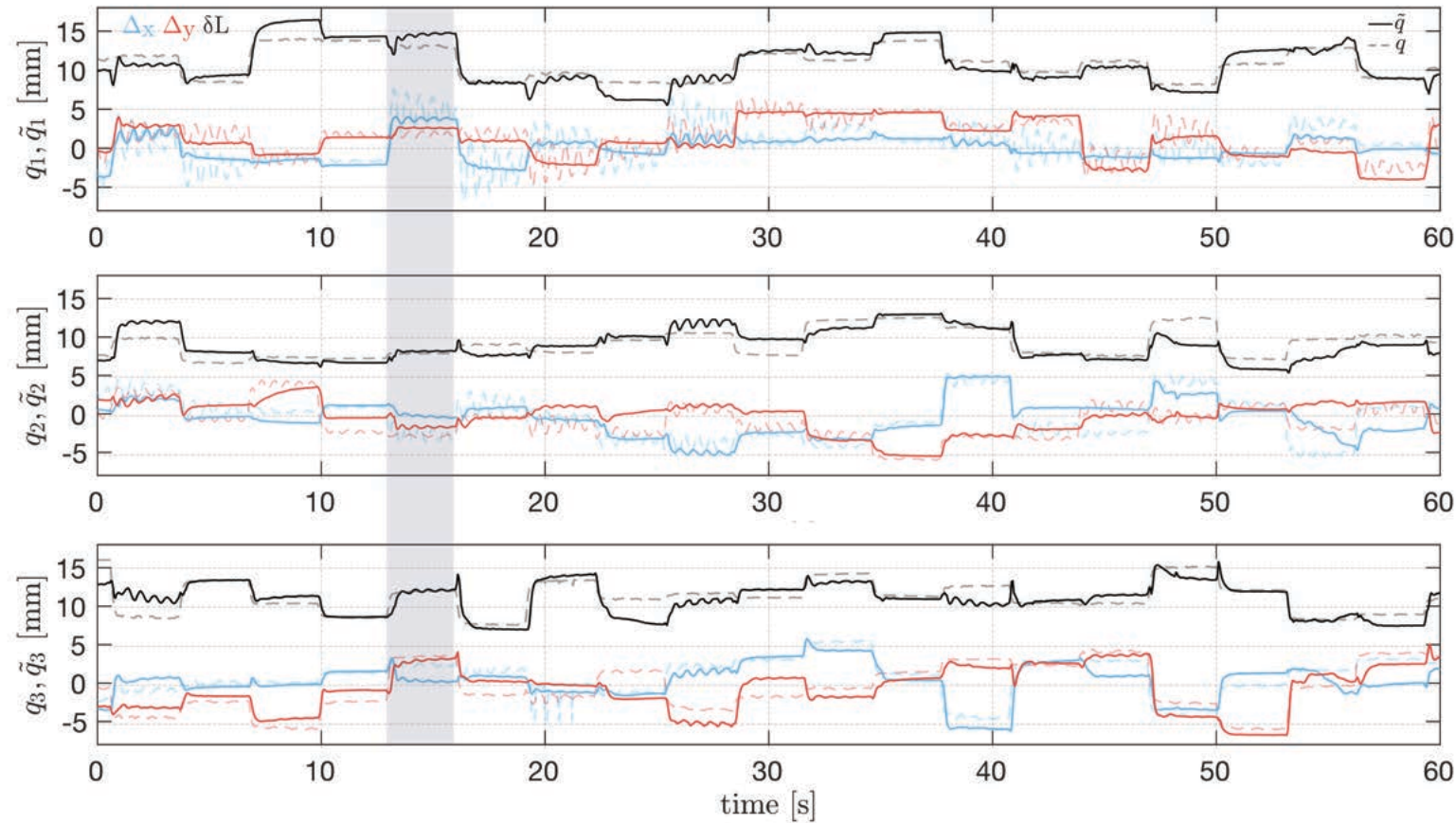


Prediction | Ground truth

Random actuations



Prediction | Ground truth

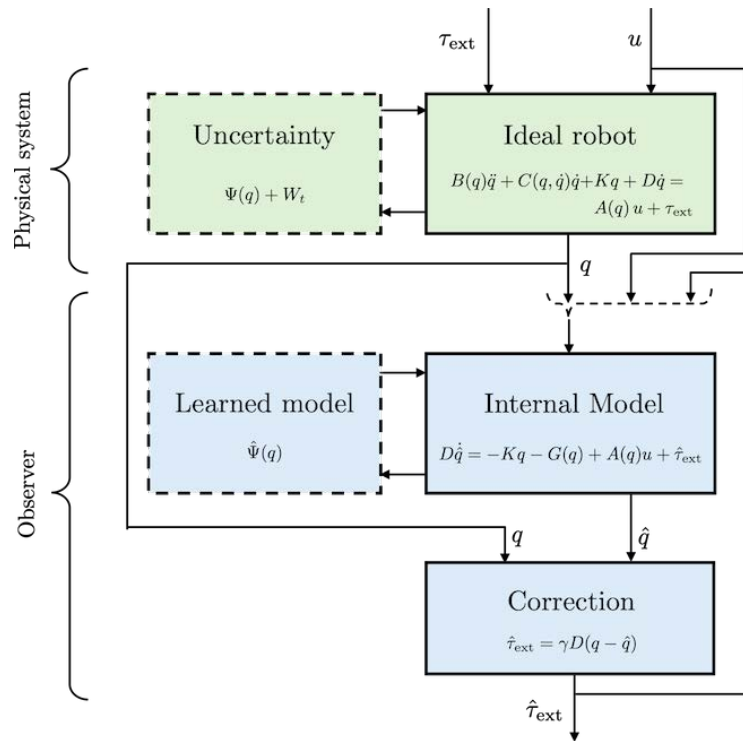


\tilde{q}_i = prediction; q_i = ground truth

- Gray bar indicates one, 3-second random actuation interval
- Dynamic motions are filtered, especially for Δ_x and Δ_y
- Short time delay observed between \tilde{q}_i and q_i
- **Dynamic behaviors are not fully captured**

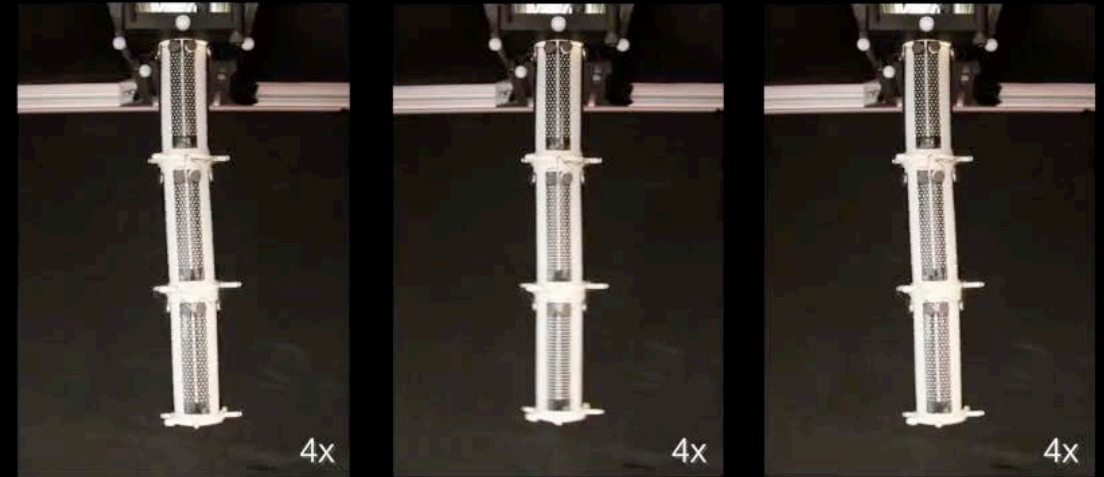
Predicted configuration approximates that at steady-state;
new sensors will improve predictions and feedback in control

Sensing Forces



$$D\dot{\hat{q}} = -Kq - G(q) + A(q)u + \hat{\Psi}(q) + \hat{\tau}_{\text{ext}},$$

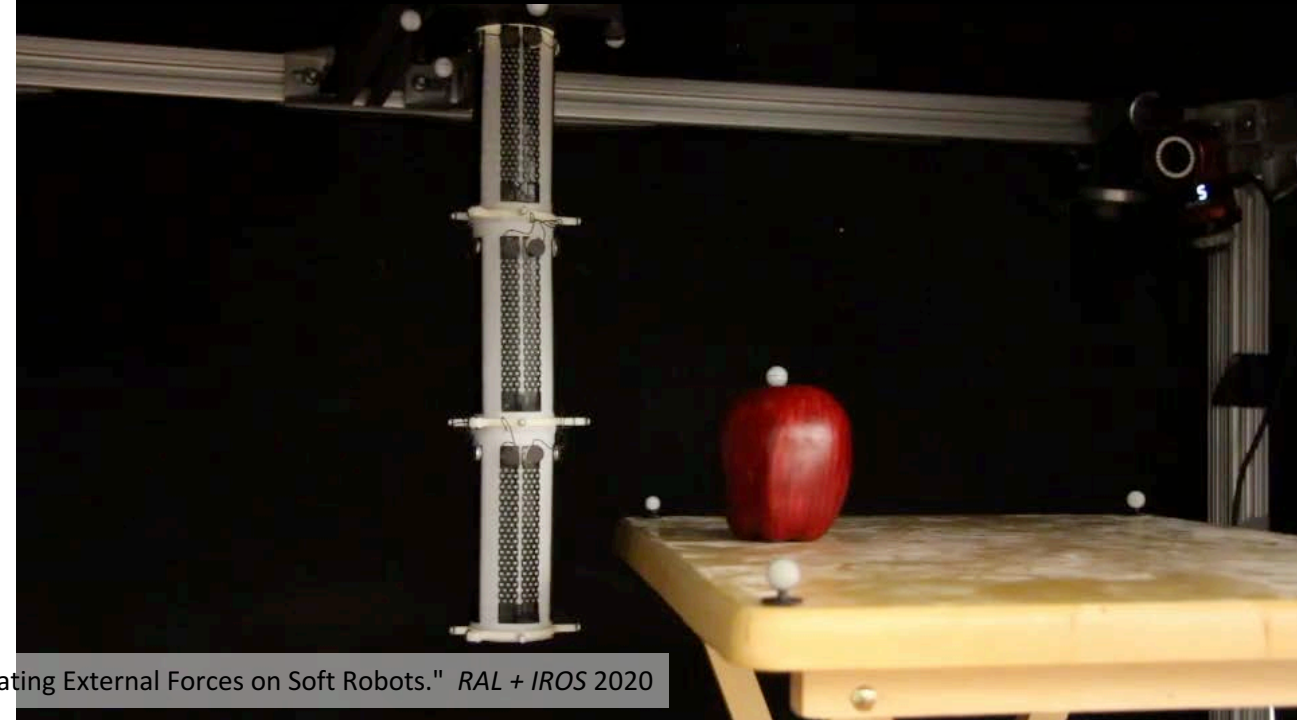
$$\hat{\tau}_{\text{ext}} = \gamma D(\hat{q} - q),$$

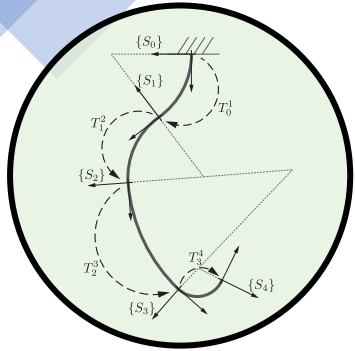


On Segment 1

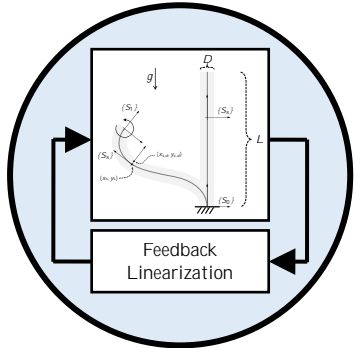
On Segment 2

On Segment 3

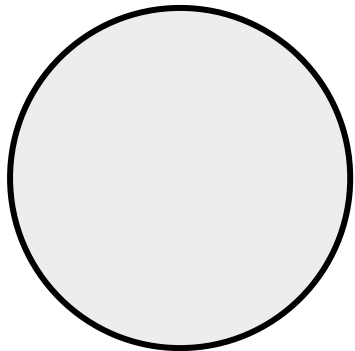




Feedback Model Based Control
Is Robust to Rough Approximations



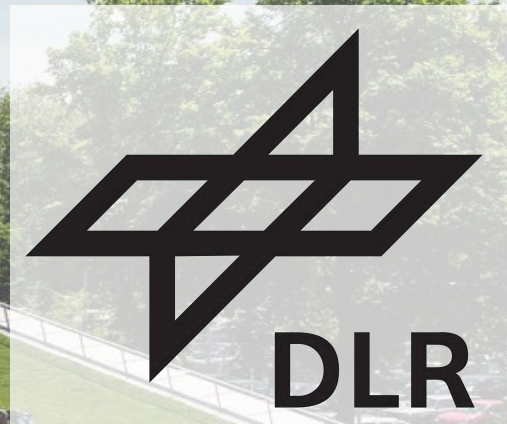
If You Want to Dig More
Do That in a Control Oriented Way



If You Want to Stick to the Simple Model,
Considered Control-Driven Ways to Improve It



TU Delft



DLR

THANK YOU!

