

Leveraging Data and the Koopman Operator to Build Control-oriented Models of Soft Robots

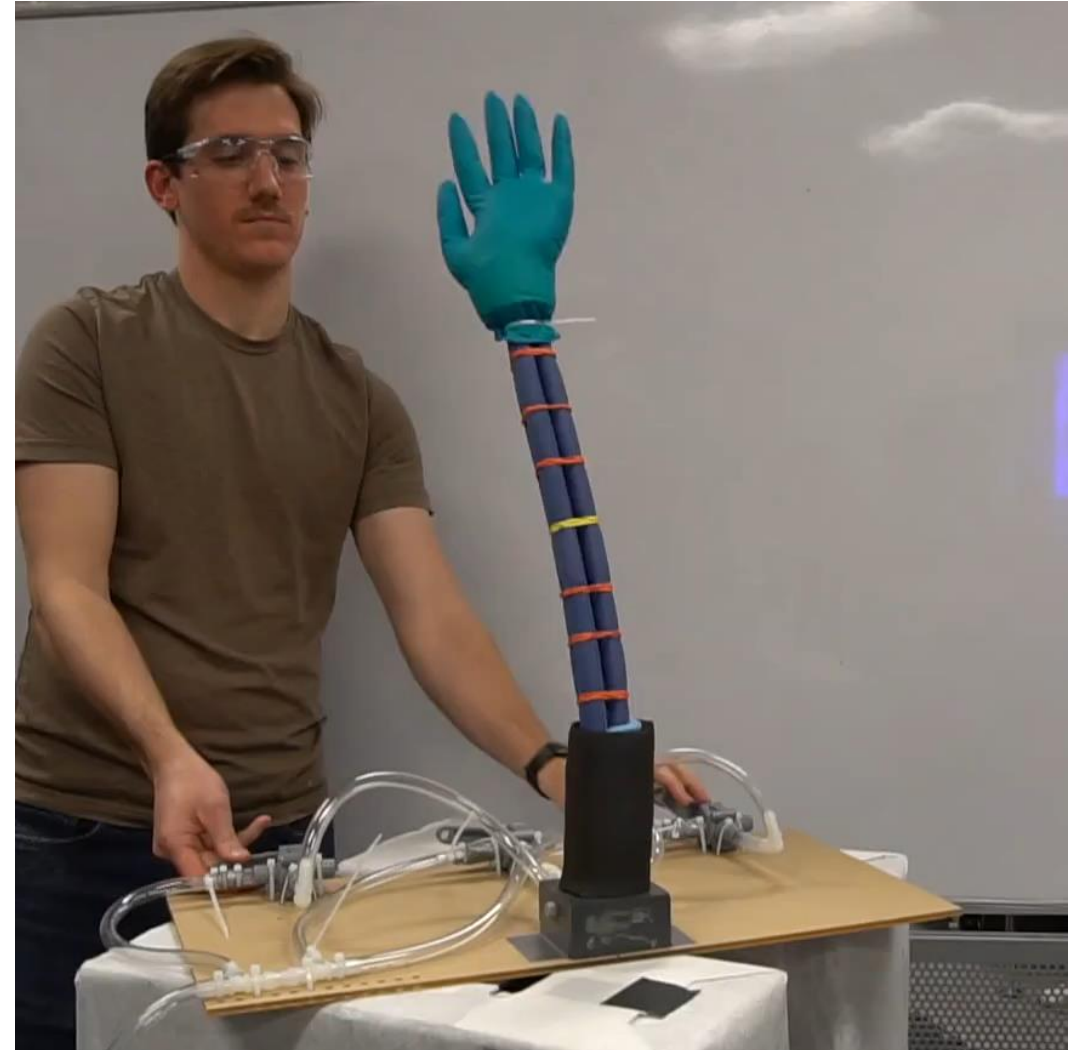
Daniel Bruder

August 7, 2020

Modeling Soft Robots: Capabilities and Limitations Workshop

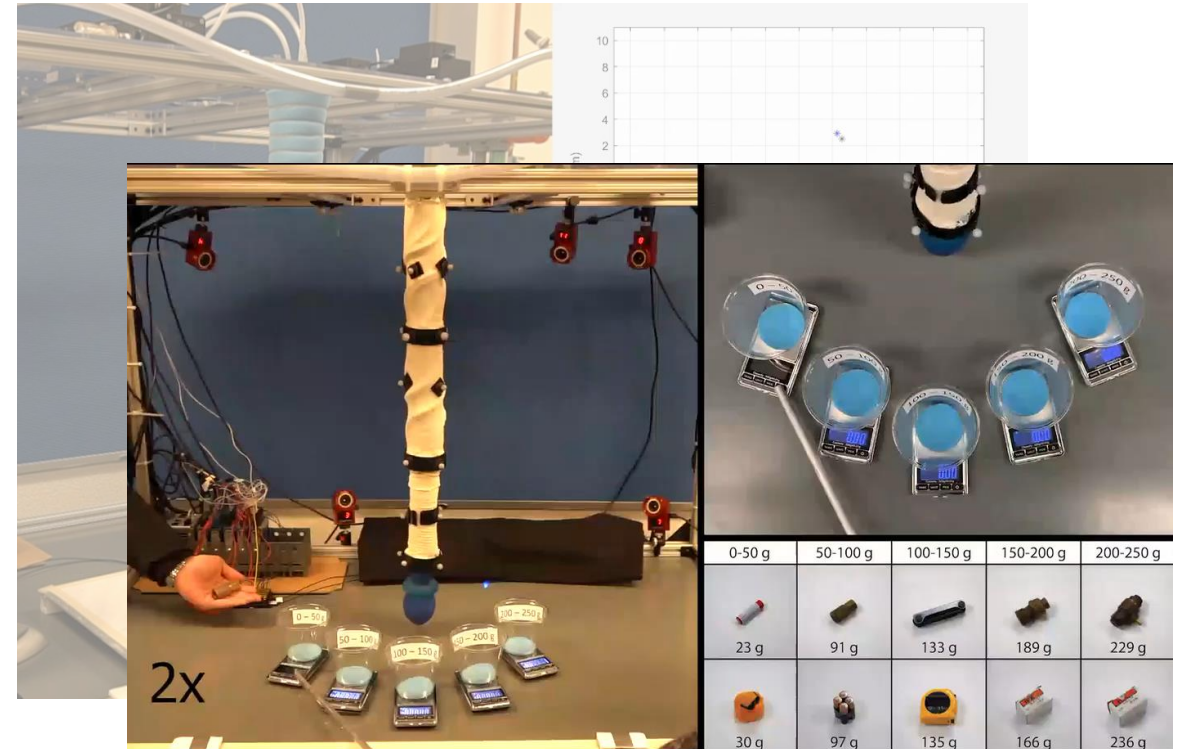
Soft robots are well suited for data-driven modeling methods

- Safe to collect data
- Avoids simplifying assumptions
- Not robot specific



Koopman-based modeling approach yields control-oriented models

- Accurate global linear representation of dynamics
- Enables real-time control
- Accommodates loading conditions

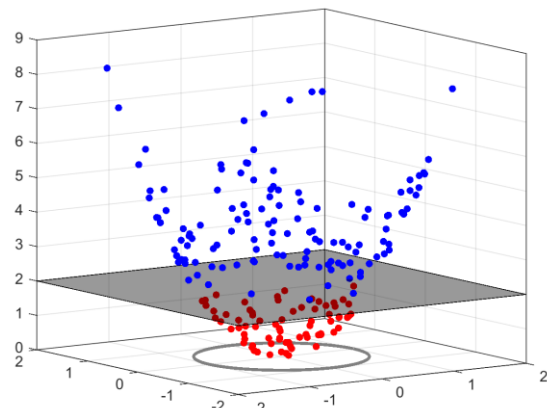


Bruder et. al. arXiv 2020

Lifting data can yield a more useful representation

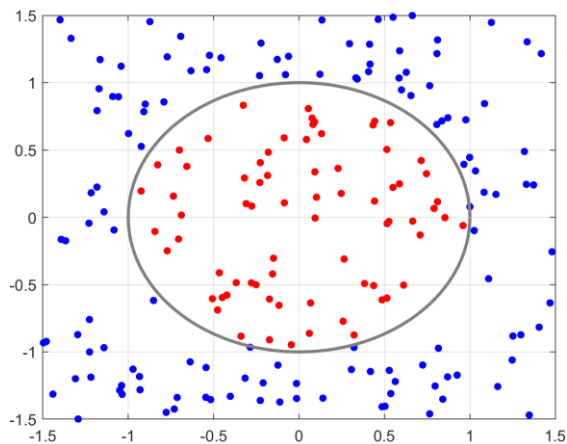
Lifted Space

Classification

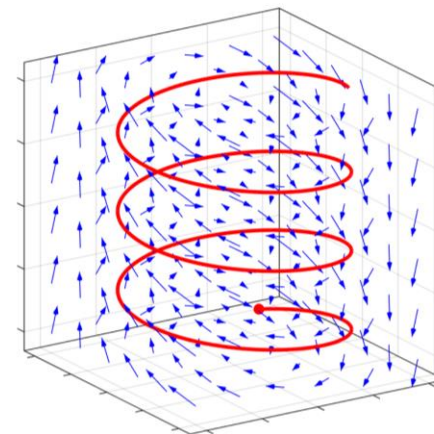


Lift $\begin{bmatrix} x \\ y \end{bmatrix} \rightarrow \begin{bmatrix} x \\ y \\ x^2 + y^2 \end{bmatrix}$

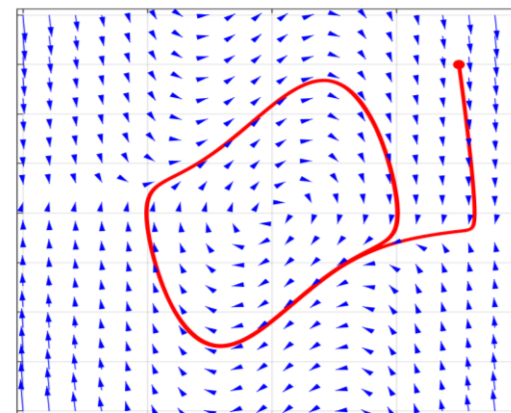
Original Space



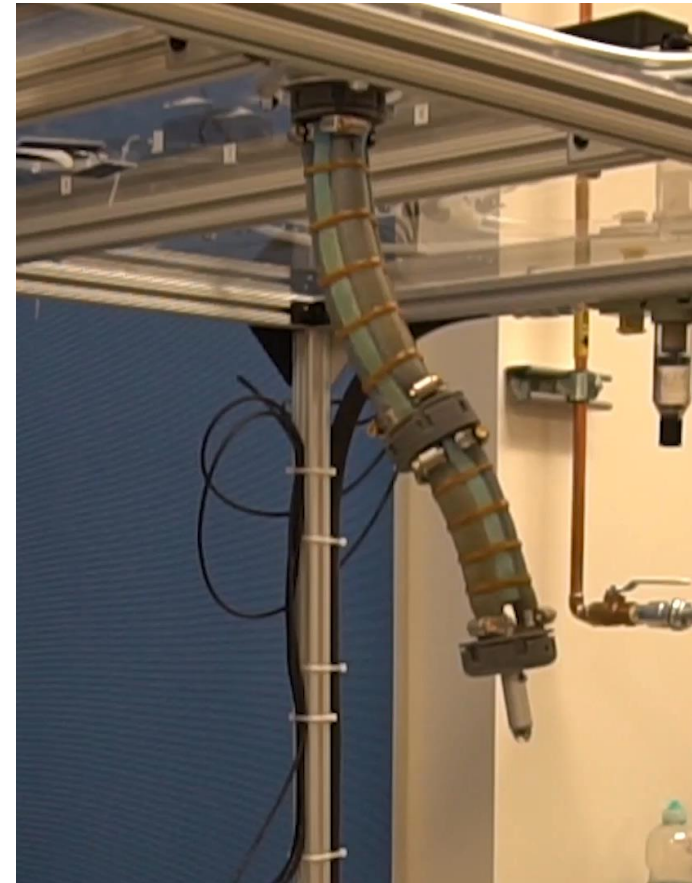
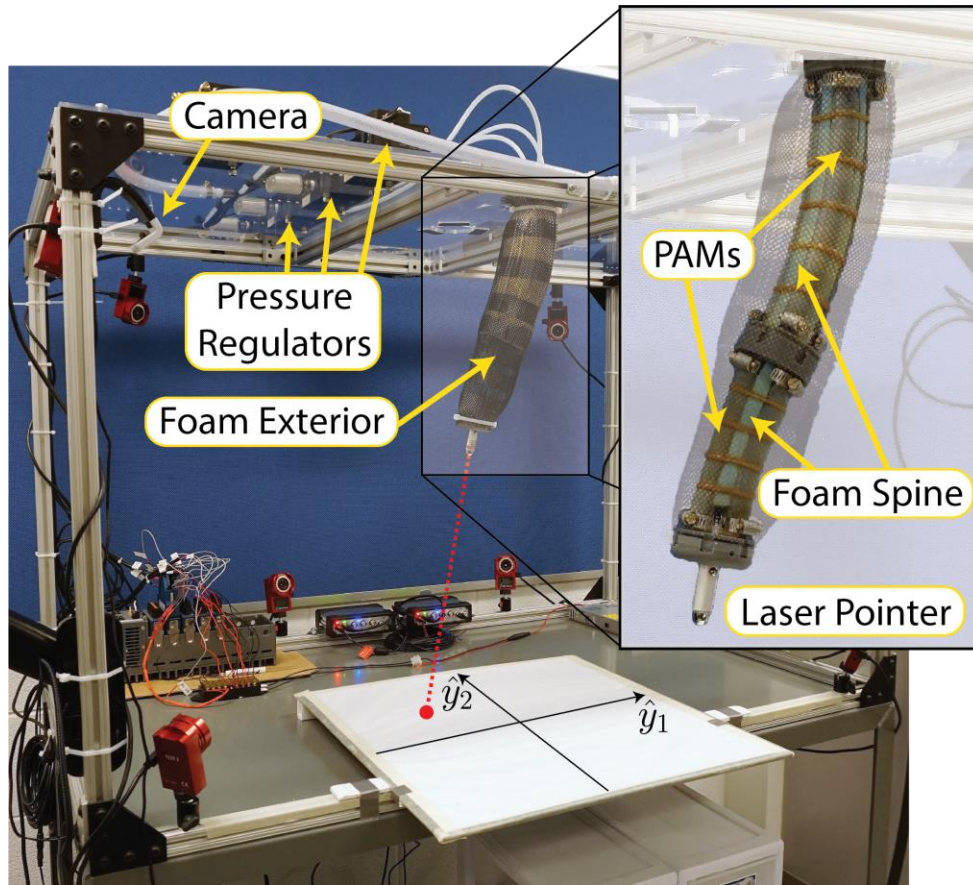
Dynamics



Lift $\begin{bmatrix} x \\ y \end{bmatrix} \rightarrow \begin{bmatrix} x \\ y \\ x^2 + y^2 \end{bmatrix}$



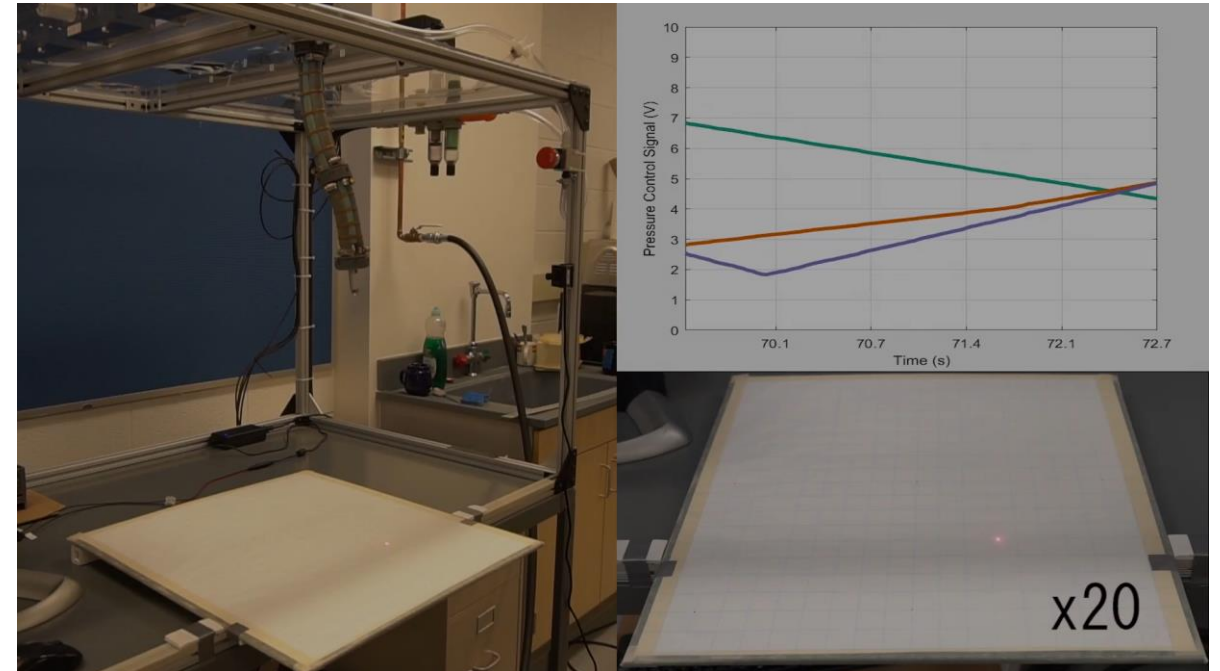
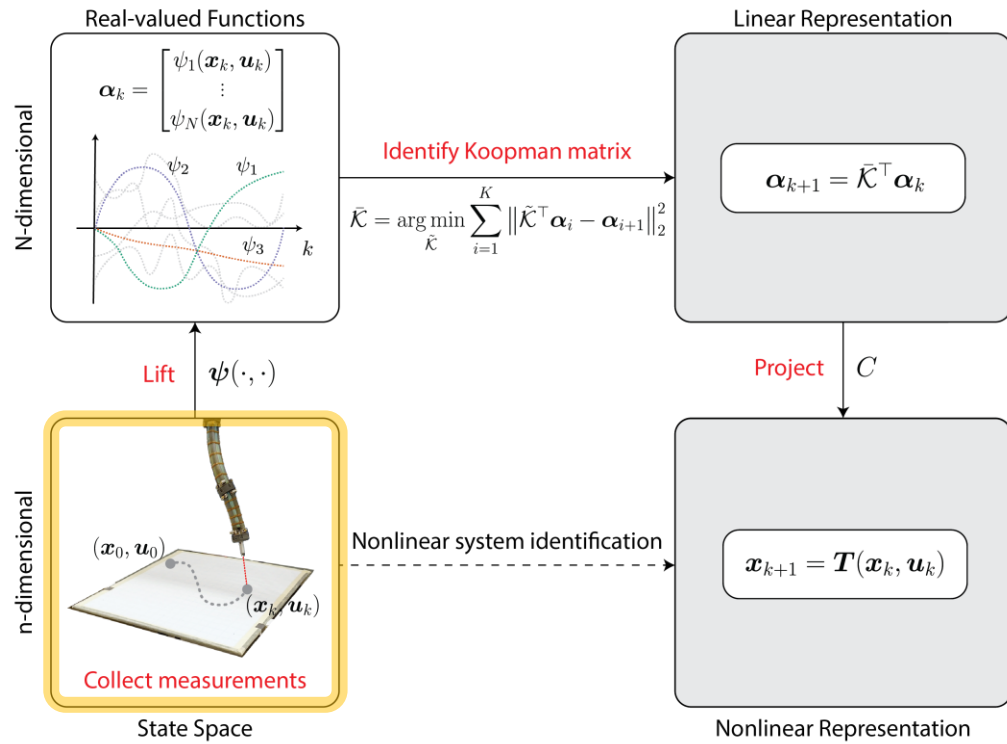
Koopman modeling approach was applied to a soft robot arm



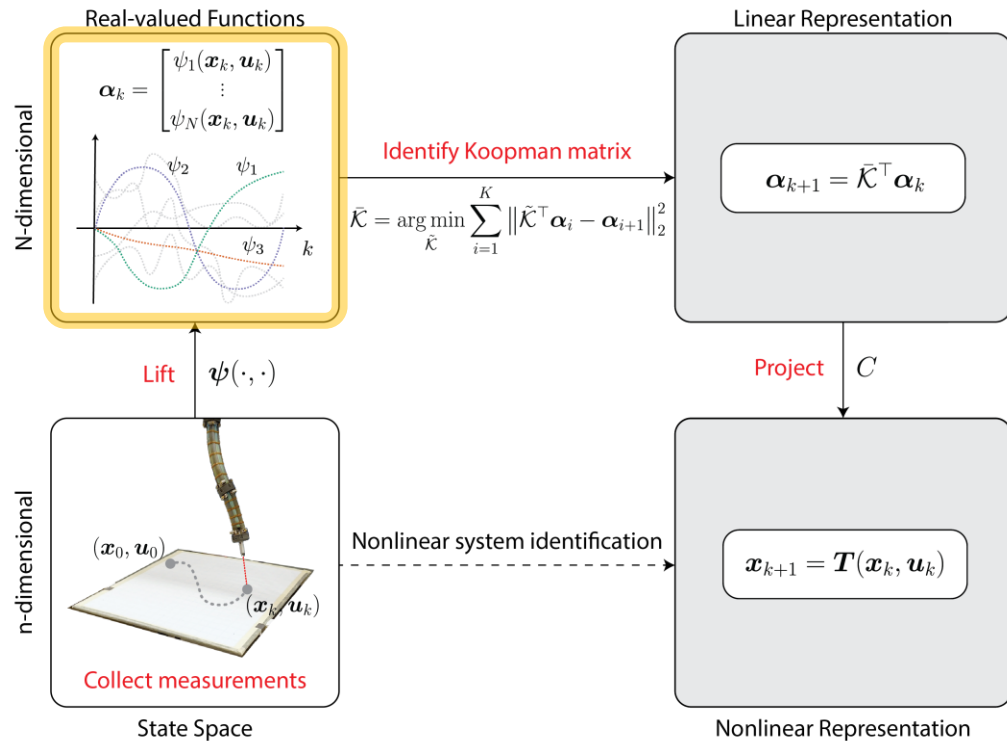
Input: Pressure regulator voltages (3D)

State: Laser dot coordinates (2D)

Data is collected under random inputs

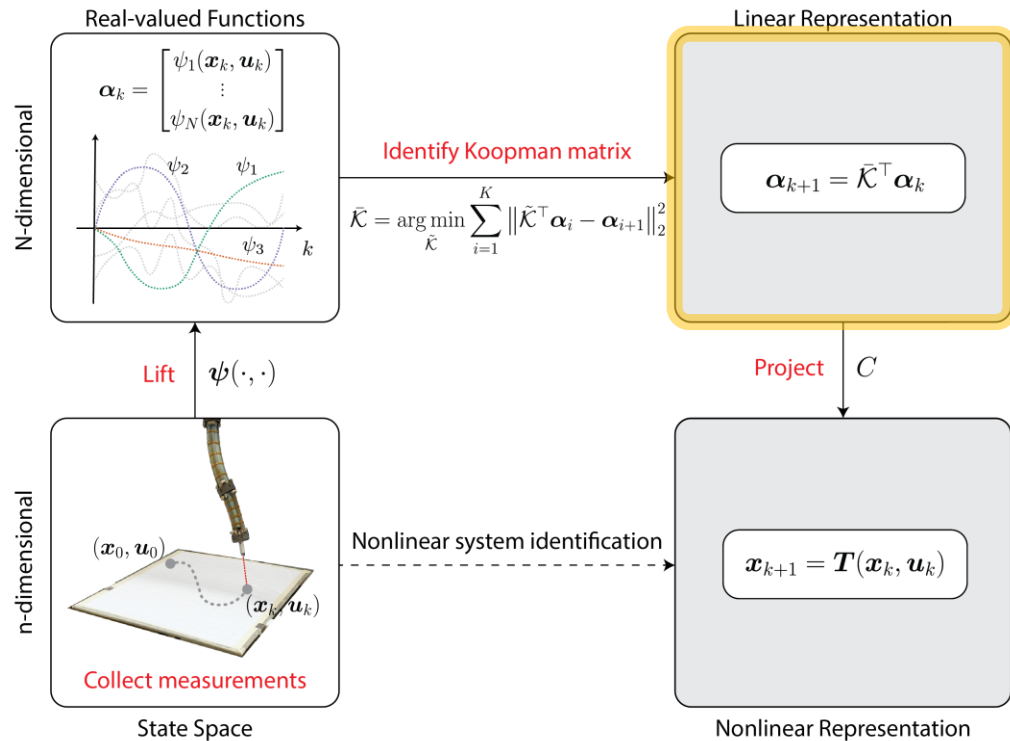


Data is lifted using polynomial basis functions



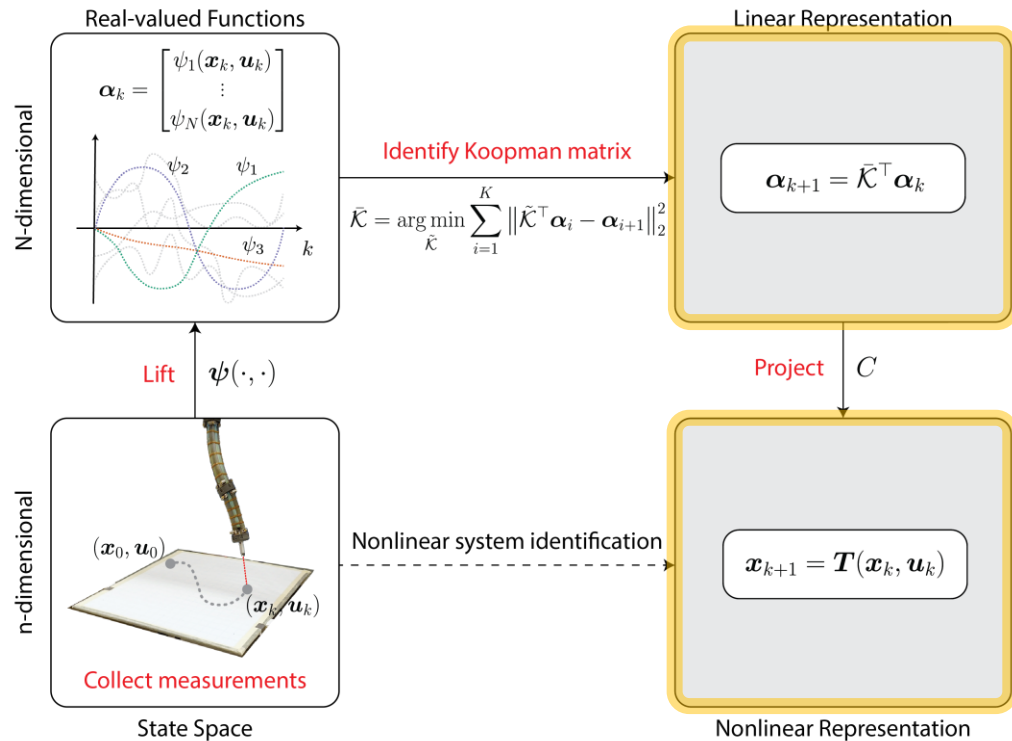
$$\psi(\mathbf{x}, \mathbf{u}) = \left[\begin{array}{c} \mathbf{x} \\ x_{[1]}^2 \\ x_{[1]}x_{[2]} \\ x_{[2]}^2 \\ \vdots \\ \mathbf{u} \end{array} \right] \left. \vphantom{\begin{array}{c} \mathbf{x} \\ x_{[1]}^2 \\ x_{[1]}x_{[2]} \\ x_{[2]}^2 \\ \vdots \\ \mathbf{u} \end{array}} \right\} \mathbf{z}(\mathbf{x}) \leftarrow \text{"lifted state"}$$

Koopman matrix is identified via linear regression



$$\bar{\mathcal{K}}^T = \begin{bmatrix} 0.973 & 0.057 & -0.034 & -0.050 & \dots \\ 0.091 & 0.812 & -0.081 & 0.120 & \dots \\ 1.000 & 0.000 & -0.000 & -0.000 & \dots \\ -0.000 & 1.000 & 0.000 & 0.000 & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

Models are constructed from the Koopman matrix



$$\bar{\mathcal{K}}^\top = \begin{bmatrix} 0.973 & 0.057 & -0.034 & -0.050 & \dots \\ 0.091 & 0.812 & -0.081 & 0.120 & \dots \\ 1.000 & 0.000 & -0.000 & -0.000 & \dots \\ -0.000 & 1.000 & 0.000 & 0.000 & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

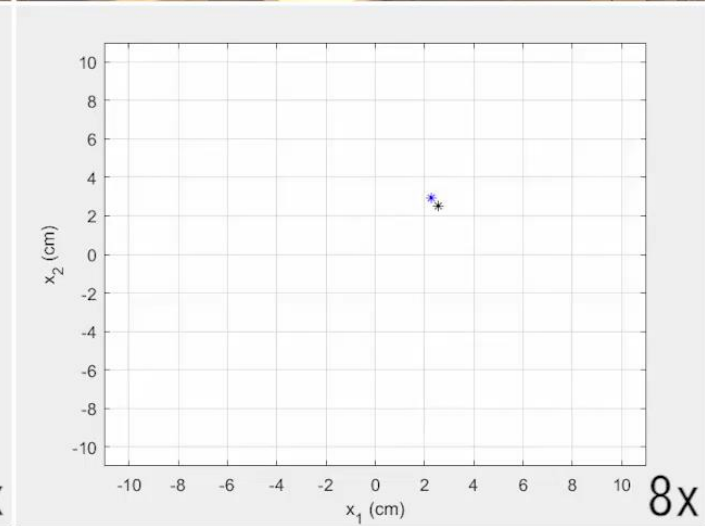
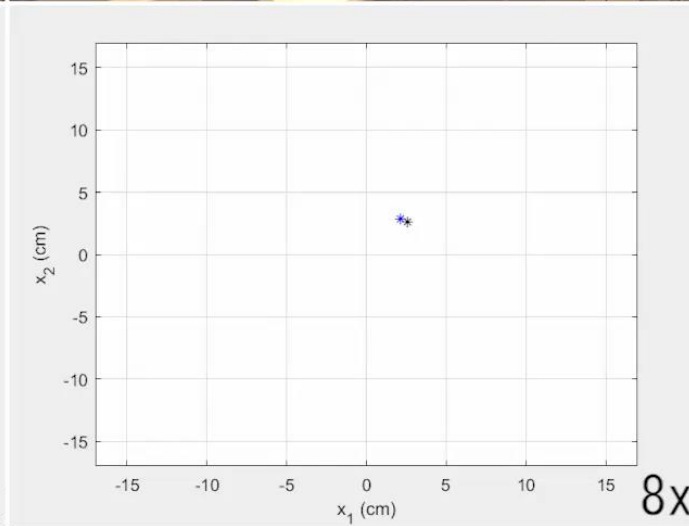
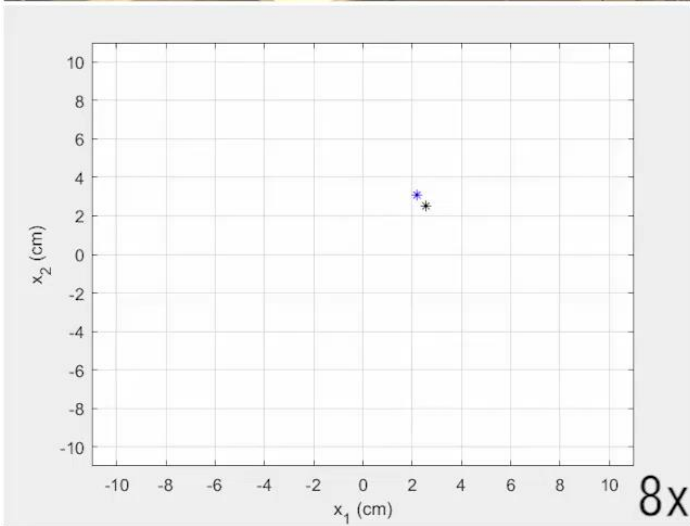
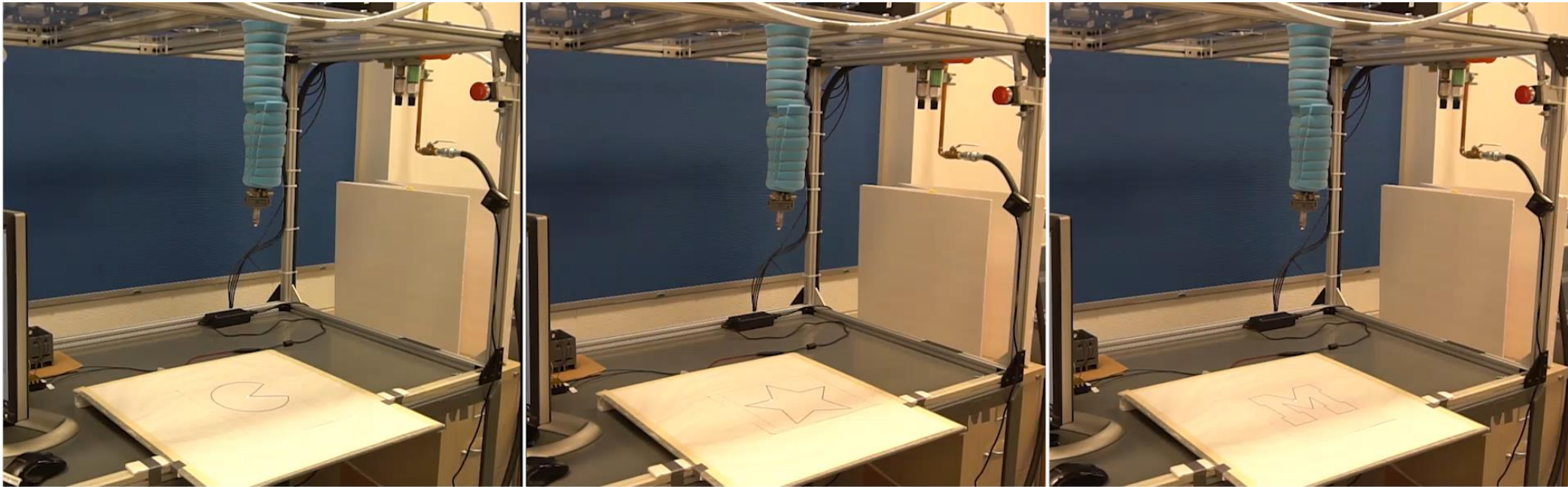
Linear Model (decomposition):

$$\bar{\mathcal{K}}^\top = \begin{bmatrix} A & B \\ \vdots & \vdots \end{bmatrix} \longrightarrow \mathbf{z}(\mathbf{x}_{k+1}) = A\mathbf{z}(\mathbf{x}_k) + B\mathbf{u}_k$$

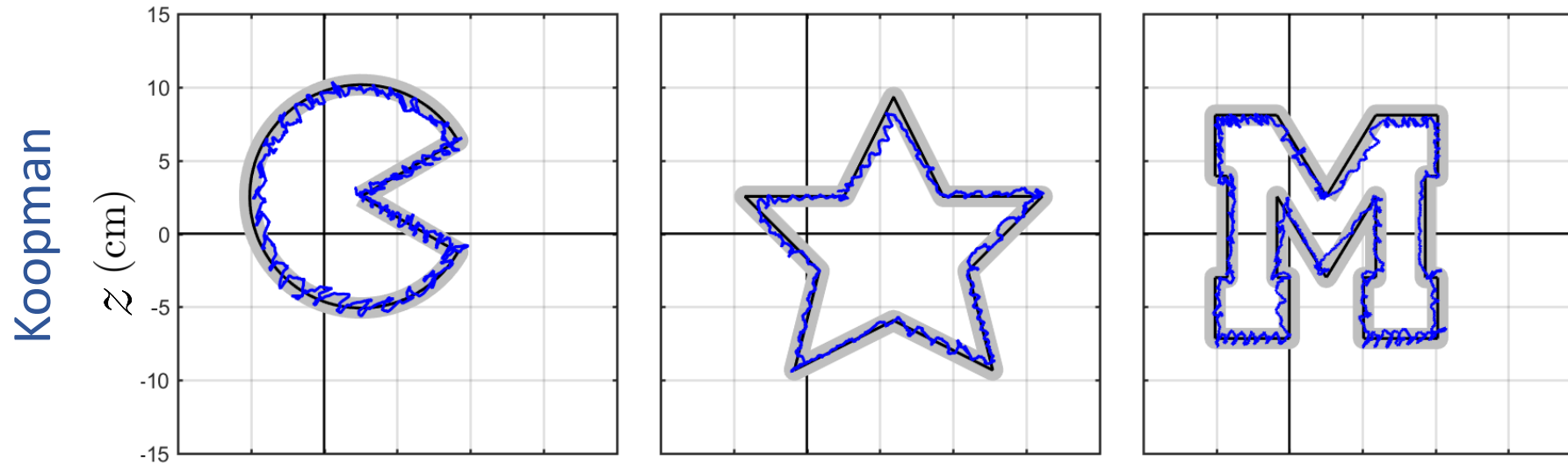
Nonlinear Model (projection):

$$\mathbf{T} = C\bar{\mathcal{K}}^\top \psi \longrightarrow \mathbf{x}_{k+1} = \mathbf{T}(\mathbf{x}_k, \mathbf{u}_k)$$

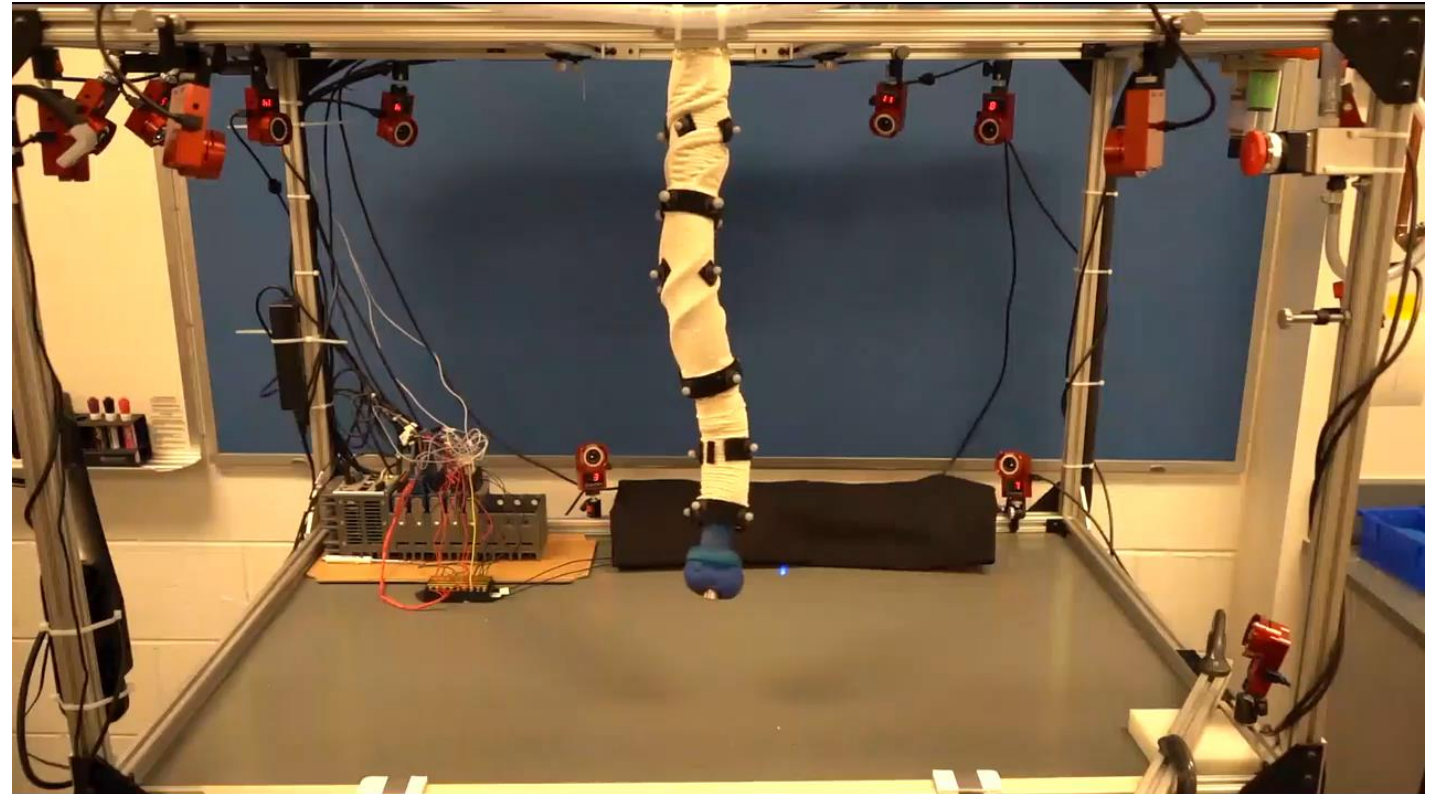
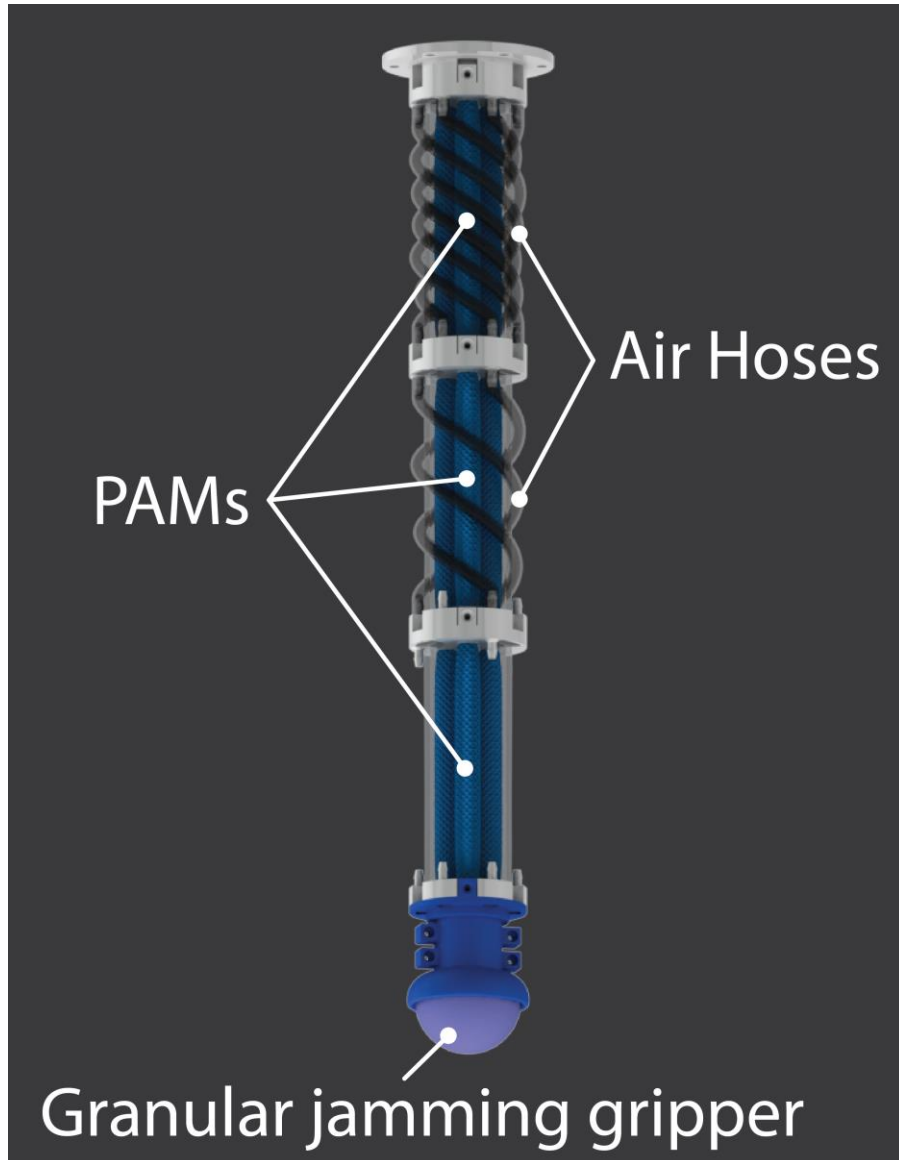
MPC controller uses linear Koopman model to make predictions



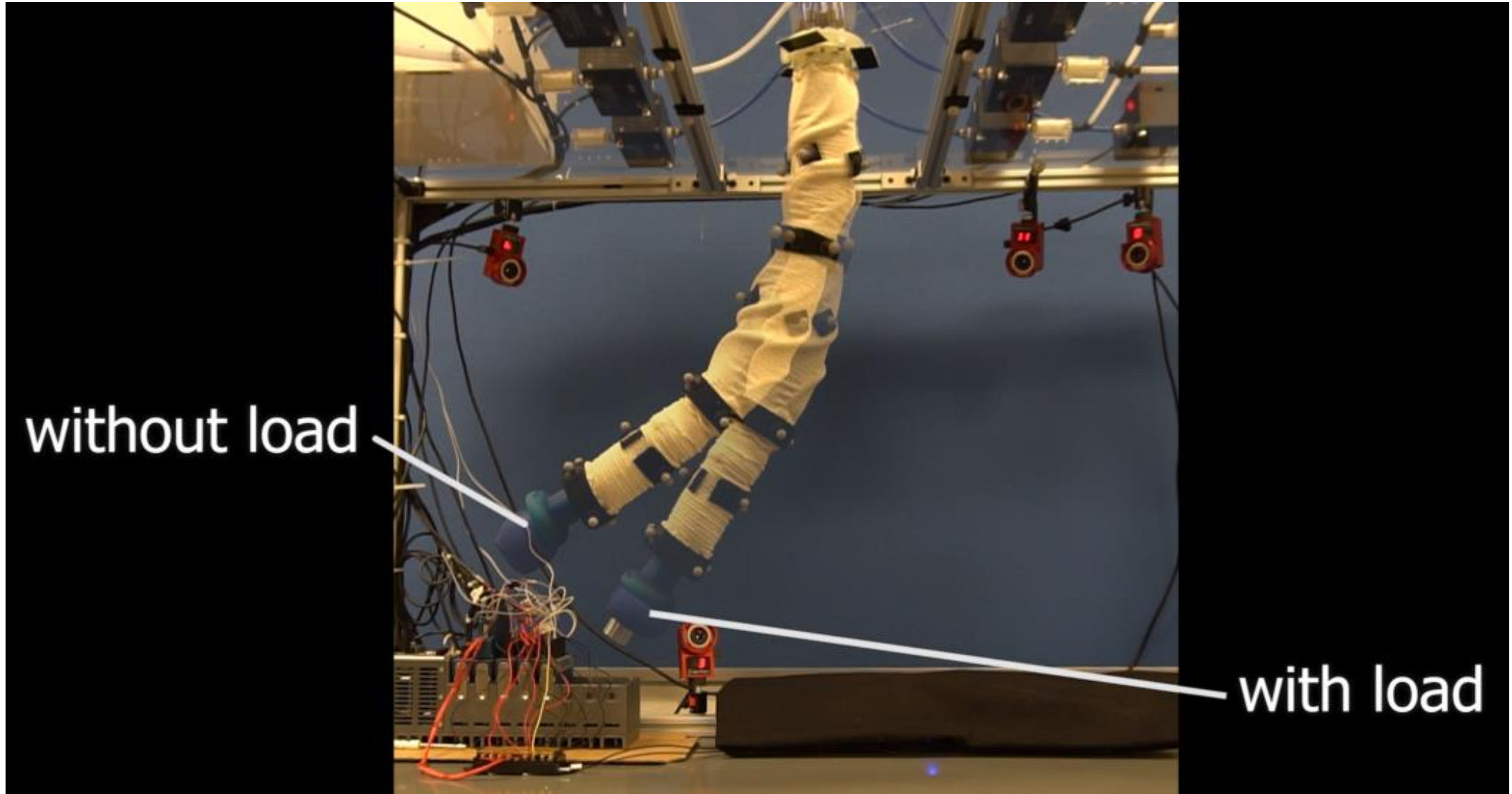
Koopman-based controller outperforms benchmark



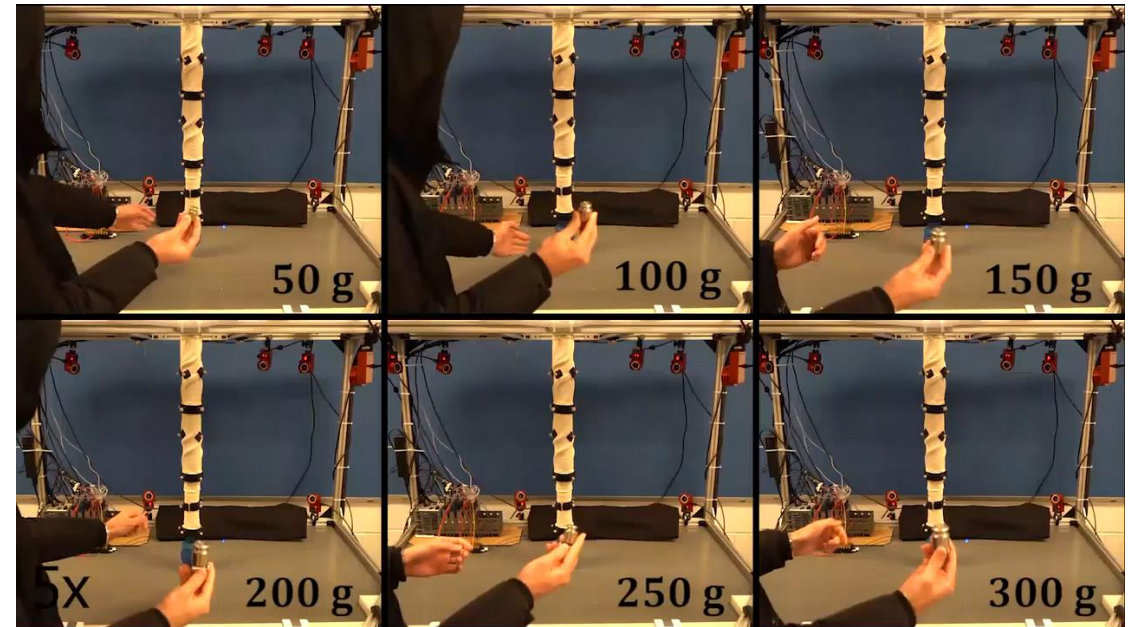
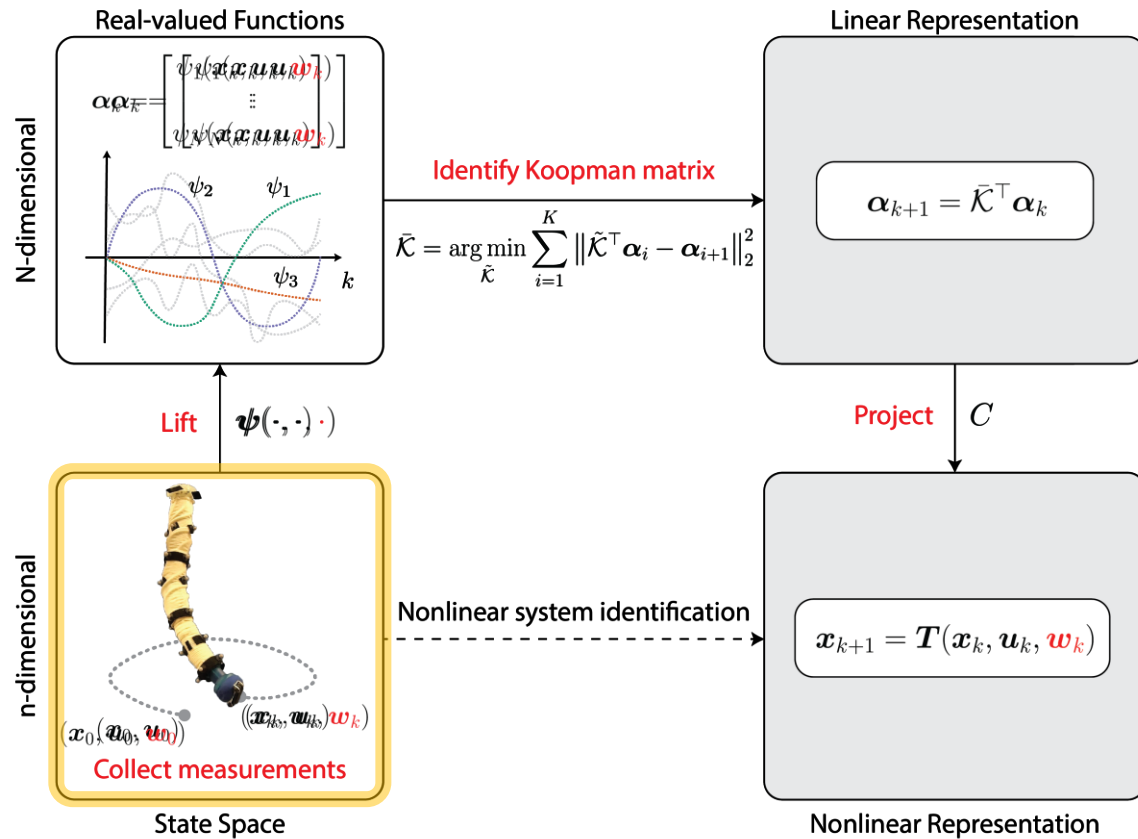
Koopman approach was applied to soft continuum manipulator



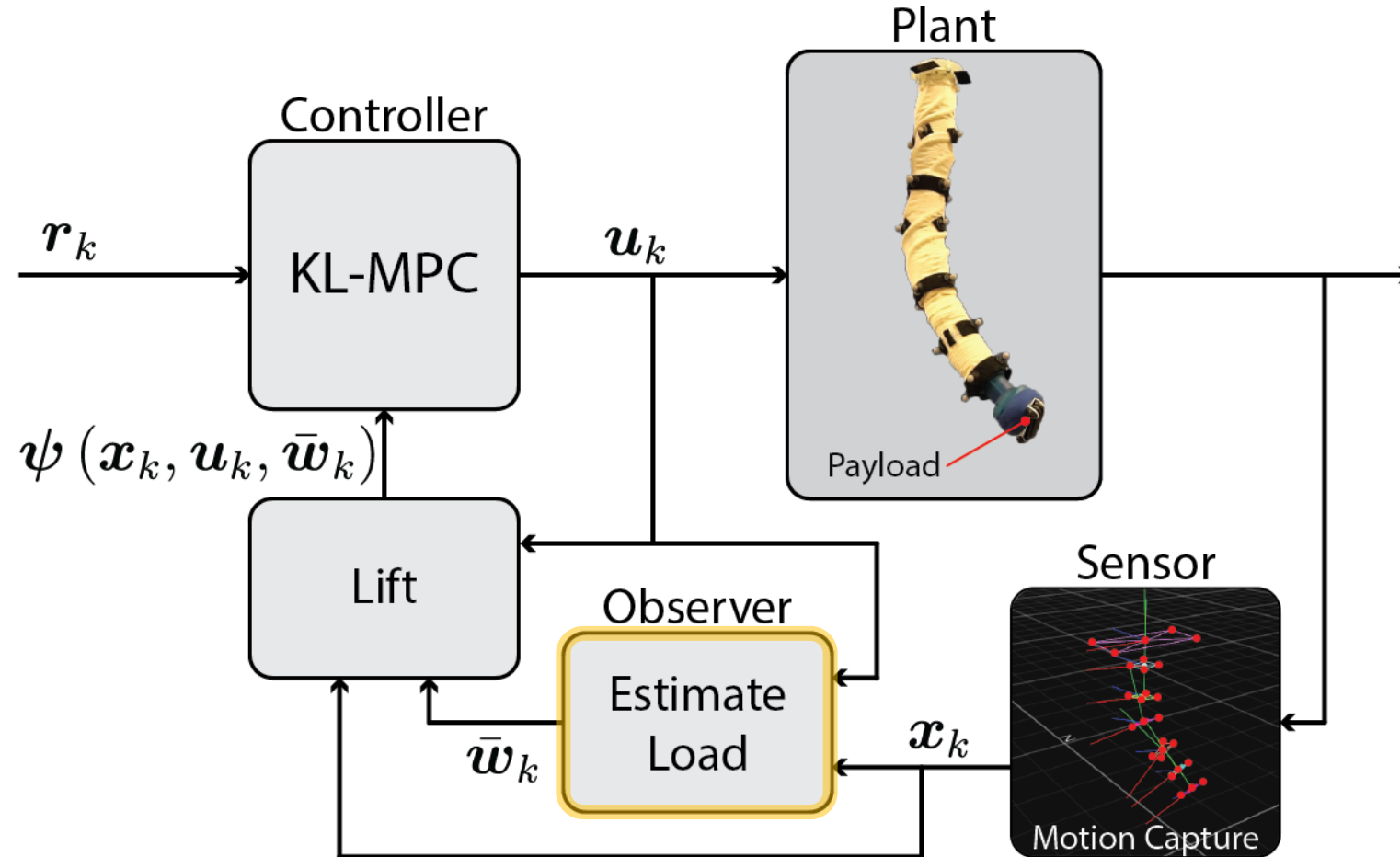
Soft manipulators deform a lot due to loading



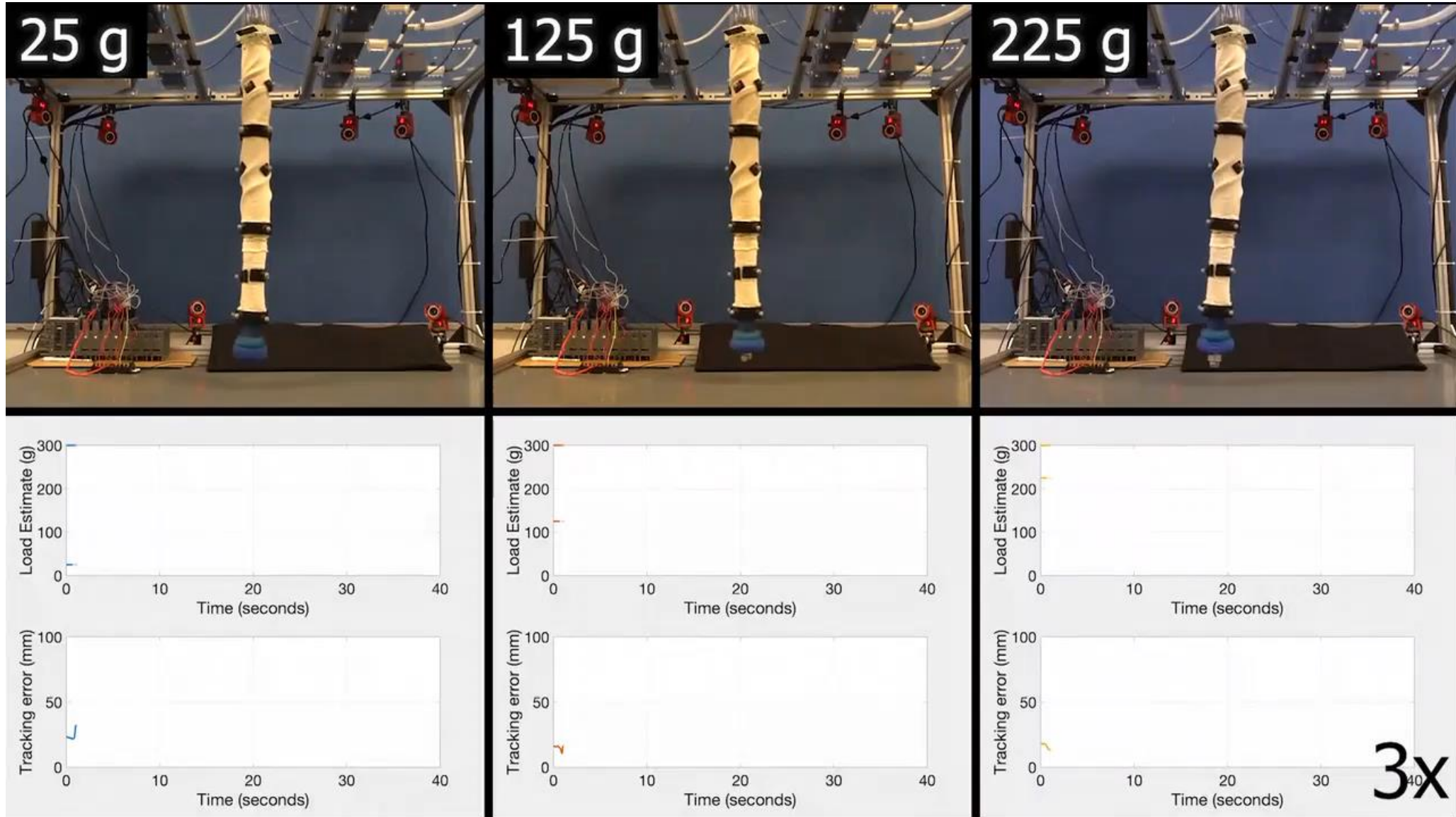
Solution: Incorporate loading into lifted model



Observer estimates load based on past measurements



As load estimate error decreases, so does tracking error



Demo: Automated object sorting by mass



Capabilities and limitations of Koopman modeling framework

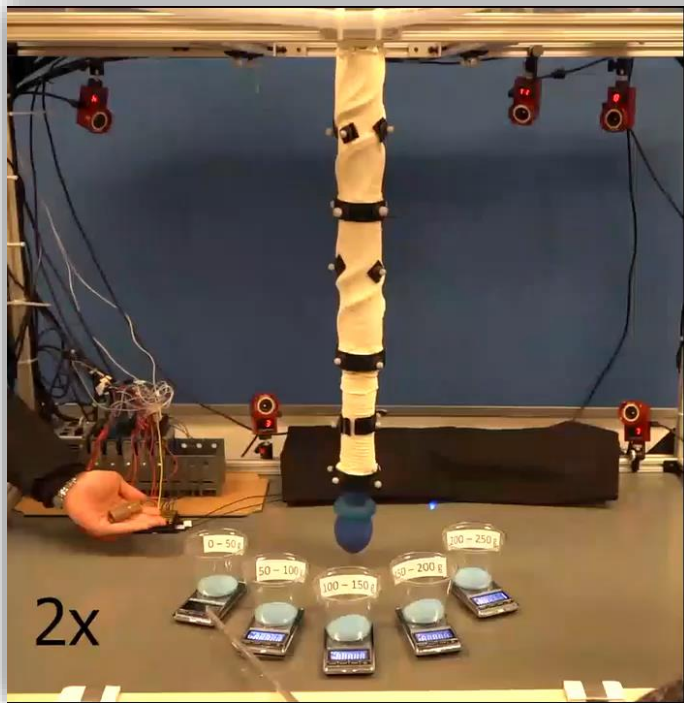
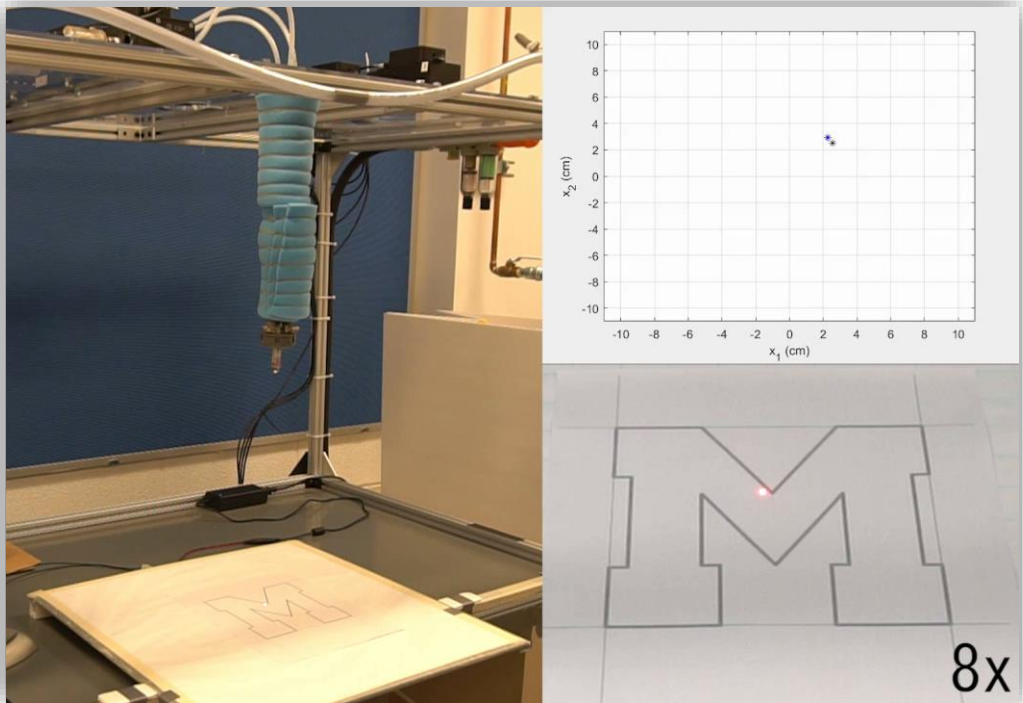
Capabilities

- Enables real-time (linear) control
- Applies to arbitrary soft robots
- Accounts for loading

Limitations (for now)

- “Curse of dimensionality”
- Depends on training data
- Does not account for contact

Thank you!



0-50 g	50-100 g	100-150 g	150-200 g	200-250 g
23 g	91 g	133 g	189 g	229 g
30 g	97 g	135 g	166 g	236 g