

Online Modeling and Control of Soft Multi-fingered Grippers via Koopman Operator Theory

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Abstract—Soft grippers are gaining momentum across applications due to their flexibility and dexterity. However, the infinite-dimensionality and non-linearity associated with soft robots challenge modeling and closed-loop control of soft grippers to perform grasping tasks. To solve this problem, data-driven methods have been proposed. Most data-driven methods rely on intensive model learning in simulation or offline, and as such it may be hard to generalize across different settings not explicitly trained upon and in physical robot testing where online control is required. In this paper, we propose an online modeling and control algorithm that utilizes Koopman operator theory to update an estimated model of the underlying dynamics at each time step in real-time. The learned and continuously updated models are then embedded into an online Model Predictive Control (MPC) structure and deployed onto soft multi-fingered robotic grippers. To evaluate the performance, the prediction accuracy of our approach is first compared against other model-extraction methods among different datasets. Next, the online modeling and control algorithm is tested experimentally with a soft 3-fingered gripper grasping objects of various shapes and weights unknown to the controller initially. Results indicate high success ratio in grasping different objects using the proposed method. Sample trials can be viewed at <https://youtu.be/i2hCMX7zSKQ>.

I. INTRODUCTION

Grasping and manipulation are fundamental functions of robotics. Traditional robotic grippers consist of a set of mostly rigid joints and links for a variety of tasks such as perching [1], [2], digging [3], [4], sorting [5], [6], and others [7], [8]. Soft grippers offer flexibility and dexterity, and have gained momentum recently (e.g., [9], [10]). Various applications have been increasingly using soft grippers, such as minimally invasive surgery [11], agriculture [12], human rehabilitation [13], as well as manufacturing techniques (3d printing [14], [15], silicone molding [16], [17], surface and shape deposition [18]), and others [19]–[21].

Soft robots (including soft grippers) have garnered significant attention and grown into an important research topic, one of the prevailing challenges relates to their modeling and control [22]. Due to the infinite degrees of freedom of soft robots, accurate first-principles-based models are hard to derive. Moreover, in most cases, system non-linearities pose additional difficulties to control design. One way to resolve such constraints is by considering data-driven methods.

Various methods based on neural networks have been proposed for modeling and control of soft grippers. The authors

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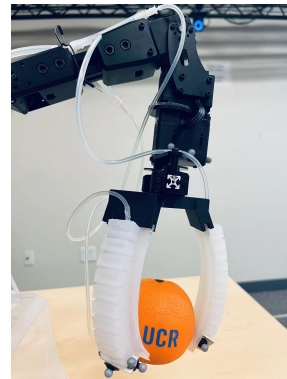


Fig. 1. Instance of the soft gripper considered herein grasping a soft ball using the proposed online learning-based method. The method is designed to be agnostic to the shape and/or weight of the object to be grasped.

in [23] show the efficiency of recurrent neural networks in terms of grasp success and stability using a shape-memory soft gripper with integrated hybrid microelectronic sensing skin. Uniformly sampled x-y positions and z axis orientations are considered as candidates in the dataset while no closed-loop control is implemented. In [24], a highly compliant multi-fingered hand is controlled by inflating or deflating chambers to demonstrate tasks that human’s hand could do, e.g., turning a valve and grasping a bottle from a table. The control algorithm is designed based on imitation learning and reinforcement learning that utilize measurements and experience to update the policy. Another work [25] tries to estimate objects’ instability and slippage due to acceleration of the robot or insufficient grasp strength using neural networks to improve grasp performance.

An alternative data-driven direction approach, which is also pursued in this paper, is based on the Koopman operator theory. The Koopman operator theory can be used to map a complicated nonlinear system into a higher-dimensional linear system approximating the unknown nonlinear dynamics directly from data. Thus, it is appropriate for modeling and control of soft robots [26]. For example, the highly nonlinear dynamics of a soft robot consisting of three pneumatically-driven actuators is identified by Koopman operator [27]. The method constructs the relationship between PWM signals corresponding to actuator pressure and position/velocity of the end-effector; learned model of this form can then be used directly for control design. In [28], Hankel Dynamic Mode Decomposition is used to estimate the Koopman operator. The learned model is then used in a Linear Quadratic Regulator (LQR) to control a soft robot arm to reach a target position. The Koopman operator theory is also implemented in the modeling of a soft robotic swimmer in simulation [29].

In this paper, we propose an online modeling and control approach for soft multi-fingered robotic grippers based on Koopman operator theory. First, dictionaries of lifting functions are designed based on the workspace of the soft gripper. Then, instead of implementing the meta-learning based Koopman identifier [30], ACD-EDMD [31] is used to learn and update the model at every time step in real-time without any complicated dictionary learning. Updated models, in turn, provide the dynamics constraints within an MPC structure to help achieve desired control objectives.

The paper's contribution are twofold:

- We propose an online modeling approach that utilizes the Koopman operator theory. An online control algorithm is designed that uses the learned and continuously-refined models in real-time and adapts control inputs for an MPC structure accordingly.
- We evaluate and compare via physical experiments the prediction accuracy of different modeling methods among different datasets using two soft grippers. The proposed online modeling and control algorithm is implemented in the grippers to grasp different objects of varying shape and weight, without any explicit information provided to the algorithm a-priori.

II. PRELIMINARY MATERIAL

A. Koopman Operator Theory and Extended Dynamic Mode Decomposition (EDMD)

The Koopman operator theory [32] details how to construct an infinite-dimensional linear operator that governs the evolution of observables $g(\xi_t)$; the latter is also called the “lifted” variables of original states ξ_t . Then, the original nonlinear system f can be represented by Koopman modes, eigenvalues and eigenfunctions. Consider the nonlinear system $\xi_{t+1} = f(\xi_t)$, with $\xi \in \mathbb{R}^{n_x}$. The evolution of observables g using Koopman operator $\mathcal{K} : \mathcal{F} \rightarrow \mathcal{F}$ can be written as $\mathcal{K}g(\xi_t) = g(f(\xi_t))$. Decomposition of the full state observable $g(\xi) = \xi$ using N Koopman modes v_n , eigenvalues λ_n and eigenfunctions φ_n , yields [33]

$$\xi_{t+1} = g(f(\xi_t)) = \mathcal{K}g(\xi_t) \rightarrow \xi_{t+1} = \sum_{n=1}^N v_n \lambda_n \varphi_n(\xi_t) . \quad (1)$$

Given state history $\Xi = [\xi_1, \xi_2, \dots, \xi_M, \xi_{M+1}]$ (commonly referred to as “snapshots”), $\mathcal{K}$ can be expressed as a finite-dimensional approximation $K : \mathcal{F}_N \rightarrow \mathcal{F}_N$ of the Koopman operator $\mathcal{K} : \mathcal{F} \rightarrow \mathcal{F}$ via EDMD. To do so, we need a dictionary of functions that lift state variables to a higher-dimensional space where observable dynamics is approximately linear.

Given a dictionary $\Psi(\xi_m) = [\psi_1(\xi_m), \dots, \psi_N(\xi_m)]$, the Koopman operator can be approximated by minimizing the total residual between snapshots, $J = \frac{1}{2} \sum_{m=1}^M (\Psi(\xi_{m+1}) - \Psi(\xi_m) K)^2$. This can be solved by truncated singular value decomposition, yielding

$$K \triangleq G^\dagger A, \text{ where } \begin{cases} G = \frac{1}{M} \sum_{m=1}^M \Psi_m^* \Psi_m , \\ A = \frac{1}{M} \sum_{m=1}^M \Psi_m^* \Psi_{m+1} , \end{cases} \quad (2)$$

with † , T and * denoting pseudoinverse, transpose and conjugate transpose, respectively. With K via (2), we obtain

$$\begin{cases} v_n = (w_n^* B)^T , \\ \lambda_n \eta_n = K \eta_n , \\ \varphi_n = \Psi_t \eta_n , \end{cases} \quad (3)$$

where η_n is the n -th eigenvector, w_n is the n -th left eigenvector of K scaled so $w_n^T \eta_n = 1$, and B is a weight matrix such that $\xi = (\Psi B)^T$ [33].

The evolution of the original nonlinear system using the estimated Koopman operator is described by replacing expressions (3) into (1). Control inputs can be readily incorporated to the definition of Ψ as an augmented state [34].

B. ACD-EDMD

One of the most critical steps that affects the performance of Koopman operator-based methods is how to choose a proper dictionary for lifting the original states, $\mathcal{D} = \text{span}\{\psi_1, \psi_2, \dots, \psi_N\}$. In our previous work [31], we have proposed ACD-EDMD as a general and analytical approach to formalize the construction of the dictionary of lifting functions based on fundamental dynamical system properties, namely the configuration space of a rigid robot and the workspace for a soft robot. Hermite polynomials are the basis functions for Euclidean spaces, whereas for non-Euclidean spaces, state variables are mapped into a higher Euclidean space. Then, the dictionary of states $D(\xi)$ is expressed as the Kronecker product of the lifting functions of all these lower-dimensional spaces. For the control input, $D(u)$ is computed by the zero- and first-order Hermite polynomials and Kronecker products thereof similarly to the $\mathbb{R}^{n_x}$ cases for states. Finally, the complete dictionary is formed as the Kronecker product between lifting functions for states and inputs, i.e. $\mathcal{D} = \text{kron}(D(\xi), D(u))$. With the proper design of the lifting functions, we can then apply the algorithm introduced before in Section II-A to extract a model of the robotic system at hand using the Koopman operator theory.

III. SOFT GRIPPER SYSTEM DESIGN AND PROPERTIES

In this work we consider soft multi-fingered robotic grippers that are pneumatically actuated. A rigid sub-system is used for gross transport and positioning of the wrist plate, which contains the soft fingers (actuators) that are responsible for object grasping (Fig. 1). Note that motion of the rigid sub-system is not included in the model we aim to learn. Instead, we only consider the grasping behavior of the soft fingers in this paper.

A. Soft Gripper Design and Integration

The soft gripper comprises three identical bending actuators [35] (Fig. 2) which are retrofitted PneuNets [36]. These actuators use pneumatic pressurization and depressurization applied to in-series connected deformable chambers to create rotational motion. The soft actuators are made via silicone (Smooth-On Dragon Skin 30) casting in 3D-printed molds (with carbon-fiber reinforced Onyx filament), and are attached to 3D-printed plates. We consider two distinct

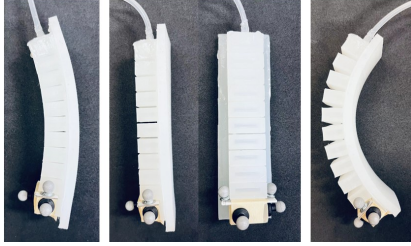


Fig. 2. Soft finger depressurized (left), idle (middle) and pressurized (right).

plates for arranging the soft fingers, one where the three fingers are arranged in a symmetric manner and one that is asymmetric (Fig. 3). The soft gripper assembly is attached to the ReactorX 150, a rigid manipulator with four links and four joints.¹ The plate acts as a wrist affixed to the manipulators endpoint.

The rigid sub-system serves a dual purpose: first to move the soft gripper to a desired position and then to lift the soft gripper after it has grasped an object. Note that the focus of this work is on the soft gripper, assessing how our proposed Koopman operator-based algorithm can enable the soft gripper to grasp objects of different shapes and weight without explicit knowledge of. To evaluate grasping success, we quantify if the gripper can hold the object as it is being lifted up by the rigid manipulator.

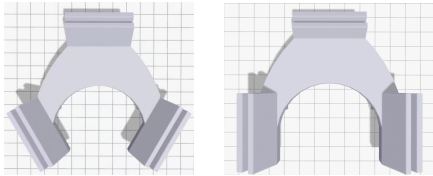


Fig. 3. CAD renderings of the rigid attachment plates considered herein that afford symmetric (left) and asymmetric (right) soft finger arrangements.

B. Pneumatic Actuation

The soft fingers are pneumatically actuated using Programmable-Air boards (Fig. 4). The board is based on the Arduino nano (ATMega328P), and has a maximum pressure of ± 50 kPa and flow rate of 2 liters/min. Pressurization is controlled by changing the PWM signal sent to pumps. Two such boards were considered for the experiments; the detailed configuration is discussed in Section V.

C. Workspace Construction

As discussed in [31], the workspace of soft robots needs to be defined to obtain the dictionary of lifting functions, which is used in the Koopman operator-based modeling approach. The workspace of a robot is the set of positions that it can reach. For soft multi-fingered grippers, the position of the tips of the fingers can be considered to construct the workspace. The state of the soft gripper is thus defined by the concatenation of the positions of each tip as $\xi_1 = [x_1, y_1, z_1]$, $\xi_2 = [x_2, y_2, z_2]$, and $\xi_3 = [x_3, y_3, z_3]$, expressed in terms of an inertial frame set at the center of the plate (Fig. 5).²

¹ The original fifth joint of the robot is a rigid pincher which is removed for the purposes of this work.

² Although this work uses a 3-fingered soft gripper, the proposed approach can be directly extended to account for general n -fingered soft grippers.

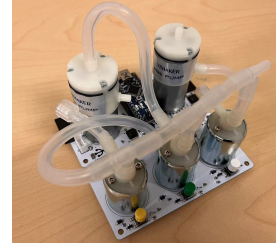


Fig. 4. The Programmable-Air Pneumatic Control Board.

We can further simplify the workspace used for operator learning by exploiting the physical constraints underlying the $\{x_i, y_i, z_i\}, i = 1, 2, 3$ state vectors. The types of actuators considered herein are constrained to create planar motion and can only bend about the normal vector to the plane they are constrained to create motion at (which is determined herein based on the arrangement of the rigid attachment plate). This way, only one of $\{x_i, y_i, z_i\}$ for each finger suffices, thus giving rise to a workspace for the whole soft gripper of $\mathbb{R}^1 \times \mathbb{R}^1 \times \mathbb{R}^1$. Without loss of generality, here we choose z_i as the representations of sub-workspace for each of the fingers, but any other state component would work as well. Besides the Kronecker product of sub-dictionaries, we also include in the library observations of other states and inputs for full-observability. We define $D_\xi = [1, z_1, z_2, z_3, z_1 z_2, z_1 z_3, z_2 z_3, z_1 z_2 z_3]$. The dictionary is computed as $D = [\xi_1, \xi_2, \xi_3, \text{kron}(\mathbf{u}, D_\xi)]$. After eliminating redundant terms, the final dictionary contains 29 terms.³

IV. ONLINE MODELING AND CONTROL

Unlike rigid robotic systems whereby it is known how to construct their dynamics, soft robotic systems possess complicated and, most often, infinite-dimensional dynamics. Thus, data-driven approaches may be a better fit for extracting models for soft robotic systems directly from data. However, models learned offline or in simulation (a technique often employed in relevant works) may be invalidated at runtime due to the presence of uncertainty [37], unless a very delicately designed experimental environment and operation process are imposed for the dynamics learned offline to remain valid for online model-based control. This process can get very tedious and is not scalable. Instead, online control should require limited data and limited time to enable online computation, which are key properties enabled via Koopman operator-based methods [30], [38]. Thus, we propose an online modeling approach using Koopman operator theory to update dynamics constraints in real time and adjust inputs accordingly within an MPC structure.⁴

³ It is beneficial to seek to construct the smallest possible dictionary that best describes the system at hand for computational expediency. At times, doing so relies on exploiting engineering intuition and/or any system symmetries. In this work we take advantage of the bending-only motion afforded by the specific fingers we consider. However, our method is general and can directly apply to any type of soft fingers that afford unconstrained position (and orientation) control of their tips in full 3D space, albeit at the expense of increasing the size of the constructed dictionary.

⁴ While we consider MPC in this work, the continuous refined learned model can be used in any other online model-based control algorithm.

A. Online Model Predictive Control (MPC) Formulation

MPC determines control inputs at each time step by solving an optimization problem among a range of prediction horizon H_p constrained by robot dynamics. The general optimization algorithm can be formulated as

$$\begin{aligned} \min_{u_i} \quad & J((u_i)_{i=0}^{H_p-1}, (\xi_i)_{i=0}^{H_p}), \\ \left\{ \begin{aligned} \xi_{i+1} &= f(\xi_i, u_i), \quad i = 0, \dots, H_p - 1, \\ \xi_0 &= \xi_{\text{initial}}. \end{aligned} \right. \end{aligned}$$

In this work, the soft grippers' dynamic constraints are obtained via ACD-EDMD in real time. In other words, at each time step, we solve an optimization problem using an updated learned model. The cost function J is usually user-designed. Herein, we set a desired trajectory r and minimize the difference between predicted states and the desired points. With these considerations in place, the MPC problem solved here at each time step t is expressed as

$$\begin{aligned} \min_{u_i} \quad & J = ((u_i)_{i=0}^{H_p-1}, (\xi_i - r_i)_{i=0}^{H_p}), \quad (4) \\ \left\{ \begin{aligned} \xi_{i+1} &= \text{ACD-EDMD}(\xi_i, u_i), \quad i = 0, \dots, H_p - 1, \\ \xi_0 &= \xi_t. \end{aligned} \right. \end{aligned}$$

B. Online Modeling and Control Algorithm

We are now ready to present the proposed online modeling and control algorithm (Alg. 1). After initialization, at each time step t , control signals are obtained from the MPC controller with the updated model constraints learned based on data from the previous time step. Then, the physical robot is driven by the control inputs and observations are collected to the online training dataset. A refined model estimated from the updated dataset via ACD-EDMD is then used to create updated dynamic constraints for the following step. The process is repeated until the control task (here grasping different objects) is achieved.

V. EXPERIMENTAL TESTING AND RESULTS

To test the efficiency of our online modeling and control algorithm, we evaluate separately modeling accuracy and control performance. First, we compare the performance of different model-estimation approaches in online and offline datasets to show the benefits of training with online observations. We further compare the ACD-EDMD based online modeling estimation accuracy with SINDy (Sparse Identification of Nonlinear Dynamical Systems (SINDy) [39]) and LSTM (Long Short-Term Memory [40]) using online training datasets. Then, we implement our online control algorithm in the soft gripper and evaluate it in grasping different objects.

Motion capture system (12-camera Prime13 Optitrack) is used to collect position data (x, y, z) of the tip of each finger. To ensure consistency among all training data, we set the origin of the inertial frame at the geometric center of the attachment plate (Fig. 5). In both of the grippers, one control board controls soft fingers 1 and 3, and the other control board controls finger 2. Thus, together with the PWM signals of two control boards, 9 states and 2 inputs of the robotic soft gripper are observed.

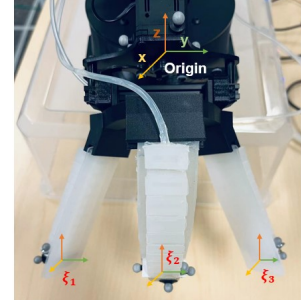


Fig. 5. Coordinate systems and motion capture marker configuration.

Algorithm 1: Online Modeling and Control

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1 initialize: Evolve the system with random valid
  inputs for the first  $M$  time steps. Then, compute the
  estimated Koopman operator from the observations:
   $K = \text{ACD-EDMD}(\{\xi\}_1^{M+1}, \{u\}_1^M)$ 
2 for  $t \geq M$  do
3   repeat
4     MPC Controller: Calculate the control inputs
      with the model constraints learned in the
      previous step by solving optimization (4).
5     Plant: Propagate the soft robotic gripper with
       $u = [u_1, u_2]$ :  $\xi_{t+1} = f(\xi_t, u)$ , where  $f$  is
      the evolving law of real plant.
6     Model: Collect new data from observations
      and update the ACD-EDMD model.
7      $t \leftarrow t + 1$ 
8   until control task is finished;
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A. Settings of Different Approaches to Compare Against

1) *SINDy*: SINDy is a data-driven approach to extract governing equations of nonlinear systems. It builds on the assumption that only a few key nonlinear candidates governing the evolution of original system. Sparse regression determines weights of those nonlinear terms from observation data. Here we adopt the example in [39] as the library $\Theta(X)$ of candidate nonlinear functions, consisting of constant, polynomial and trigonometric terms, that is

$$\Theta(X) = [1 \quad X \quad X^2 \quad \sin(X) \quad \cos(X)].$$

The sparse regression problem is solved by least absolute shrinkage and selection operator (LASSO) [41].

2) *LSTM*: LSTM is an artificial recurrent neural network that offers feedback connections and the ability to deal with entire datasets rather than single data points. LSTM networks have been used in robotics applications (e.g., [42]), notably in-hand robotic manipulation [43]. In this paper, we use the LSTM layer in MATLAB R2020a Deep Learning Toolbox to construct the network. A single layer of 20 hidden units is applied as designed in [23].

B. Model Estimation Accuracy

Different datasets for training are collected as follows.

- 1) **Unloaded Offline training data:** In offline training, constant PWM signals are given by the control board. Each signal lasts for 16 sec with a sampling rate

TABLE I
PREDICTION ACCURACY OF DIFFERENT APPROACHES

Method	Dataset	MSE($ \xi_1 $)	MSE($ \xi_2 $)	MSE($ \xi_3 $)	(magnitude)
SINDy	Offline (Unloaded)	[0.00, 556.66, 0.062]	[340.17, 0.44, 188.47]	[12.84, 327.78, 0.014]	$\times 10^3$
ACD-EDMD	Offline (Unloaded)	[0.26, 256.62, 5.76]	[180.83, 7.12, 133.35]	[7.91, 141.33, 0.69]	$\times 10^2$
SINDy	Offline (Loaded)	[364.17, 38.57, 0.74]	[0.95, 0.99, 26.59]	[122.65, 0.13, 3.25]	$\times 10^1$
ACD-EDMD	Offline (Loaded)	[211.90, 75.52, 0.0026]	[0.43, 0.13, 0.47]	[62.36, 15.21, 0.05]	$\times 10^0$
SINDy	Online	[0.0047, 0.0113, 0.0006]	[1.36, 1.24, 0.09]	[0.44, 0.0022, 0.03]	$\times 10^0$
LSTM	Online	[0.58, 1.40, 0.0136]	[0.38, 0.76, 0.60]	[1.45, 1.81, 0.87]	$\times 10^{-2}$
ACD-EDMD	Online	[0.32, 2.16, 1.58]	[0.17, 0.93, 0.20]	[0.40, 1.35, 0.15]	$\times 10^{-4}$

of 2 Hz (0.5 sec). Preliminary testing revealed that the finger can function effectively when the PWM is within the range of 20% to 35%. Thus, we collect the position and voltage signals data by either pressurizing or depressurizing all the fingers when the gripper is unloaded within that range. A total number of 32 sets are collected as the ‘Unloaded Offline’ training data. A moving-average filter with window size of 5 is applied to the offline training data.

- Loaded Offline training data:** Data from four trials of grabbing plush oranges (object 1 in Fig. 6), two trials of grabbing the smaller rectangular box (object 2 in Fig. 6) and two trials of grabbing the larger square box (object 3 in Fig. 6) are collected with length of 26 points for each trial. The ‘Loaded Offline data’ case is constructed as a combination of these 8 data sets.
- Online training data:** Online observations are collected when the gripper attempts to grasp the plush orange. Let N_T be the training data length; every $\xi_{t-N_T-1}^t$ observations are used to predict ξ_{t+1} .

The three aforementioned datasets are used to predict ξ_{t+1} for the whole online data trial of length L . We calculate the Mean Squared Error (MSE) between predicted (superscript p) and true (superscript t) states per $MSE = \frac{1}{L-N_T} \sum_{N_T}^L ([\xi_1^p, \xi_2^p, \xi_3^p] - [\xi_1^t, \xi_2^t, \xi_3^t])^2$ for the whole trajectory. Results are contained in Table I. For all algorithms, predictions computed from the offline *loaded* data are more accurate than those made based on *unloaded* data. Further, **online** approaches lead to significantly smaller error than all **offline** approaches.

We also compare the efficiency of all methods with online training data by evaluating repeated grasping of object 1 for 8 times to avoid bias. We tested all three approaches with different training data size, $N_T = \{3, 5, 10\}$.

Results are depicted in Table II (training time) and Fig. 7 (prediction accuracy). Our algorithm can run $2\times$ and $3\times$ **orders of magnitude faster** than SINDy and LSTM, respectively, per each time step. This performance is attainable because ACD-EDMD leverages fundamental characteristics of the dynamical system at hand (herein the workspace of the soft gripper) which leads to a simultaneously smaller and more descriptive dictionary to use. Further, with reference to Fig. 7, our method can achieve similar accuracy with LSTM for smaller training data size, and comparable

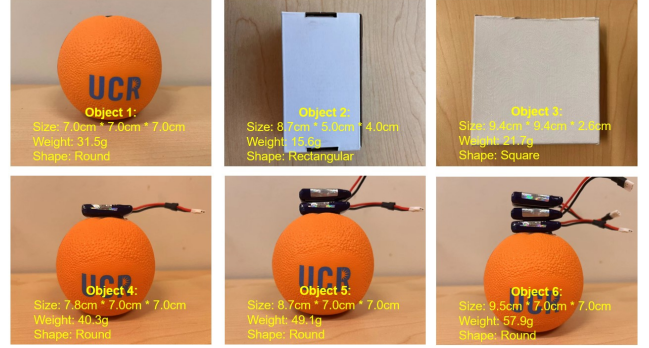


Fig. 6. Objects of different shape and/or weight considered in this work. Sample trials can be viewed at <https://youtu.be/i2hCMX7zSKQ>.

accuracy for larger training data size. (More specifically, our method can lead to more variable accuracy compared to LSTM for $N_T = 10$, but mean values are close.) The combination of comparable accuracy but substantially faster training time makes our proposed approach appropriate for online learning-based modeling and control tasks.

TABLE II
TRAINING TIMES PER EACH TIME STEP FOR DIFFERENT APPROACHES

Training Size \ Approach	ACD-EDMD	SINDy	LSTM
$N_T = 3$	0.00028 s	0.0260 s	0.7240 s
$N_T = 5$	0.00030 s	0.0583 s	0.7837 s
$N_T = 10$	0.00044 s	0.1542 s	0.8468 s

The bottom row panels of Fig. 7 show that the prediction error obtained by SINDy is much larger than the other two approaches.⁵ SINDy’s worse than expected performance may be because of the small training data size used in the online procedure, or perhaps the choice of candidate nonlinear functions selected based on the original publication [39]. This is in fact one key point of departure from SINDy in that it requires selection of candidate nonlinear functions and that selection can affect the overall performance.

C. Online Modeling and Control: Grasping

For the final evaluation of our method, we apply Alg. 1 to grasp objects using the two soft grippers with different finger configurations. The online training size N_T is 5 and the prediction horizon H_p is set at 3. In this experiment,

⁵ For error bars to be visible, we omitted those of SINDy in $N_T = \{3, 5\}$.

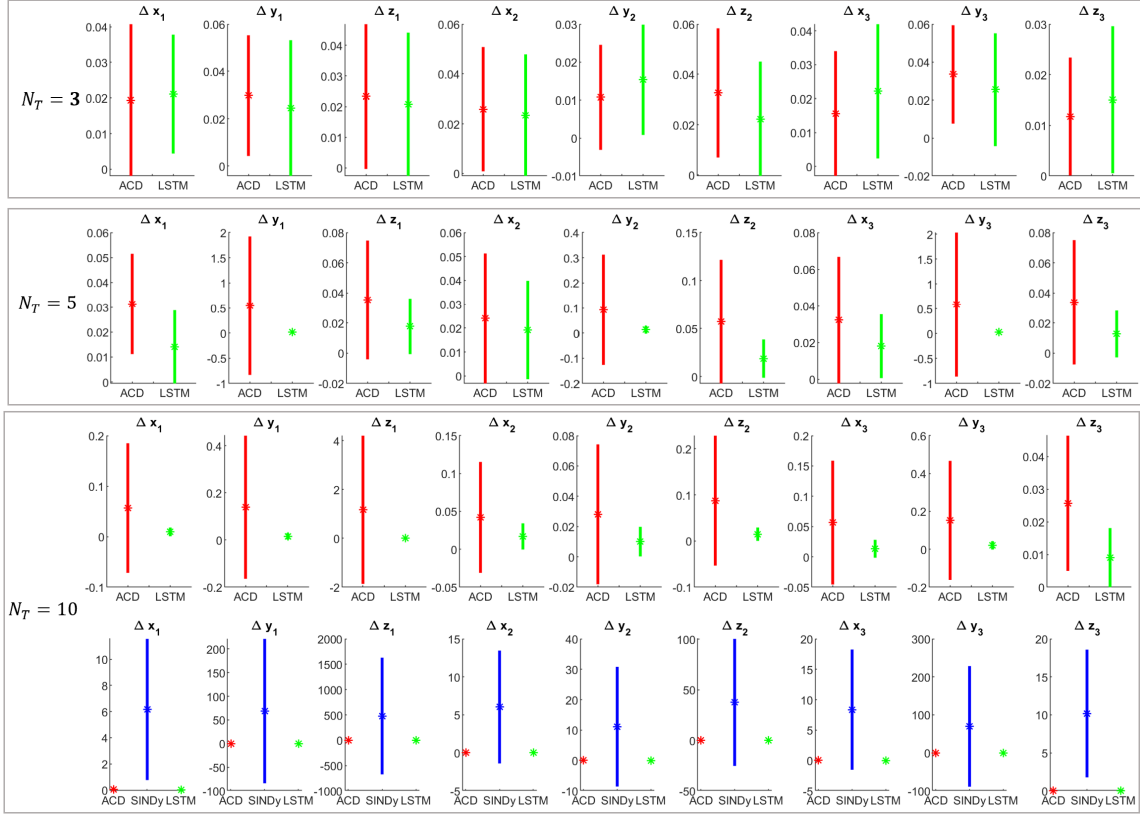


Fig. 7. 1- σ error prediction accuracy of all online methods. SINDy (blue) has large errors; to keep the bars visible, one case ($N_T = 10$) is shown.

we manually designed desired trajectories for each finger.⁶ The same desired trajectory is used for grasping objects of different shape and same shape but different weight (Fig. 6), without any information about the objects. Each grasping task is repeated 10 times to avoid bias. Successful grasps are considered those that the gripper grasps the object, holds it until fully lifted and keeps it for 3 sec after lifting.

Results show that the asymmetric gripper functions better than the symmetric one in terms of grasping heavier objects, whereas the symmetric gripper performs better on grasping objects of varying shape (Table III). However, we can still deduce that our algorithm can be easily implemented into different robots to grasp different objects without requiring any knowledge about the robot and the objects.

VI. CONCLUSIONS

Soft multi-fingered grippers have been gaining momentum across applications. However, because of their infinite-dimensionality and non-linearities, necessary modeling and control algorithms are difficult to derive. The online modeling and control method proposed in this paper relies on Koopman operator theory for data-driven modeling and online MPC for control. Our proposed method can achieve solid prediction accuracy while training significantly faster compared to related data-driven methods currently in-use.

⁶ Note that this experiment is only one example to show how our online modeling and control approach can be implemented in practice. Other model-based controllers and desired trajectories can be used as well, and one can embed our online modeling method into their design directly, which is one key benefit of our proposed method.

TABLE III

SUCCESS RATES OF GRASPING DIFFERENT OBJECTS

Object	1	2	3	4	5	6
Gripper	Symmetric Gripper					
Success Rate	100%	100%	90%	10%	0%	0%
Gripper	Asymmetric Gripper					
Success Rate	90%	80%	100%	90%	70%	0%

Our method can be directly embedded into model-based online control of robotics systems, without requiring explicit knowledge of system dynamics except for their configuration space or workspace. Results by testing with two soft 3-fingered robotic grippers attest that our method can grasp a variety of objects of different shape and/or weight without any a-priori knowledge. This work can be beneficial in applications like smart manufacturing and precision agriculture.

Future work aims to combine the online modeling approach with other model-based controllers (e.g., [44]), and develop an approach for generating and adapting online the desired trajectories to grasp a wider range of objects.

REFERENCES

- [1] S. B. Backus, L. U. Odhner, and A. M. Dollar, “Design of hands for aerial manipulation: Actuator number and routing for grasping and perching,” in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2014, pp. 34–40.
- [2] S. Liu, W. Dong, Z. Ma, and X. Sheng, “Adaptive aerial grasping and perching with dual elasticity combined suction cup,” *IEEE Robotics and Automation Letters (RAL)*, vol. 5, no. 3, pp. 4766–4773, 2020.

- [3] Z. Tong, Y. H. Ng, C. H. Kim, T. He, and J. Seo, "Dig-grasping via direct quasistatic interaction using asymmetric fingers: An approach to effective bin picking," *IEEE Robotics and Automation Letters (RAL)*, vol. 6, no. 2, pp. 3033–3040, 2021.
- [4] D. Danfeng, M. Yan, G. Xiurong, and L. Huaimin, "Research on a forestation hole digging robot," in *IEEE International Conference on Intelligent Computation Technology and Automation (ICICTA)*, vol. 2, 2010, pp. 1073–1076.
- [5] M. Gupta and G. S. Sukhatme, "Using manipulation primitives for brick sorting in clutter," in *IEEE International Conference on Robotics and Automation (ICRA)*, 2012, pp. 3883–3889.
- [6] Q. Wu, M. Li, X. Qi, Y. Hu, B. Li, and J. Zhang, "Coordinated control of a dual-arm robot for surgical instrument sorting tasks," *Robotics and Autonomous Systems*, vol. 112, pp. 1–12, 2019.
- [7] C. Mucchiani and M. Yim, "Dynamic grasping for object picking using passive zero-dof end-effectors," *IEEE Robotics and Automation Letters (RAL)*, vol. 6, no. 2, pp. 3089–3096, 2021.
- [8] C. H. Kim and J. Seo, "Shallow-depth insertion: Peg in shallow hole through robotic in-hand manipulation," *IEEE Robotics and Automation Letters (RAL)*, vol. 4, no. 2, pp. 383–390, 2019.
- [9] J. Shintake, V. Cacucciolo, D. Floreano, and H. Shea, "Soft robotic grippers," *Advanced materials*, vol. 30, no. 29, p. 1707035, 2018.
- [10] M. E. Giannaccini, I. Georgilas, I. Horsfield, B. Peiris, A. Lenz, A. G. Pipe, and S. Dogramadzi, "A variable compliance, soft gripper," *Autonomous Robots*, vol. 36, no. 1, pp. 93–107, 2014.
- [11] G. Rateni, M. Cianchetti, G. Ciuti, A. Menciaschi, and C. Laschi, "Design and development of a soft robotic gripper for manipulation in minimally invasive surgery: a proof of concept," *Meccanica*, vol. 50, no. 11, pp. 2855–2863, 2015.
- [12] E. Navas, R. Fernández, D. Sepúlveda, M. Armada, and P. Gonzalez-de Santos, "Soft gripper for robotic harvesting in precision agriculture applications," in *IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC)*, 2021, pp. 167–172.
- [13] H. Zhang, Y. Wang, M. Y. Wang, J. Y. H. Fuh, and A. S. Kumar, "Design and analysis of soft grippers for hand rehabilitation," in *ASME International Manufacturing Science and Engineering Conference (MSEC)*, vol. 50756, 2017, p. V004T05A003.
- [14] C. Tawk, A. Gillett, M. in het Panhuis, G. M. Spinks, and G. Alici, "A 3d-printed omni-purpose soft gripper," *IEEE Transactions on Robotics (T-RO)*, vol. 35, no. 5, pp. 1268–1275, 2019.
- [15] Z. Wang, D. S. Chathuranga, and S. Hirai, "3d printed soft gripper for automatic lunch box packing," in *IEEE International Conference on Robotics and Biomimetics (ROBIO)*, 2016, pp. 503–508.
- [16] S. Liu, F. Wang, Z. Liu, W. Zhang, Y. Tian, and D. Zhang, "A two-finger soft-robotic gripper with enveloping and pinching grasping modes," *IEEE/ASME Transactions on Mechatronics (TMECH)*, vol. 26, no. 1, pp. 146–155, 2020.
- [17] J. Zhou, S. Chen, and Z. Wang, "A soft-robotic gripper with enhanced object adaptation and grasping reliability," *IEEE Robotics and automation letters (RAL)*, vol. 2, no. 4, pp. 2287–2293, 2017.
- [18] S. A. Suresh, D. L. Christensen, E. W. Hawkes, and M. Cutkosky, "Surface and shape deposition manufacturing for the fabrication of a curved surface gripper," *Journal of Mechanisms and Robotics*, vol. 7, no. 2, p. 021005, 2015.
- [19] G. Gao, C.-M. Chang, L. Gerez, and M. Liarokapis, "A pneumatically driven, disposable, soft robotic gripper equipped with multi-stage, retractable, telescopic fingers," *IEEE Transactions on Medical Robotics and Bionics (T-MRB)*, vol. 3, no. 3, pp. 573–582, 2021.
- [20] E. Roels, S. Terryn, J. Brancart, G. Van Assche, and B. Vanderborght, "A multi-material self-healing soft gripper," in *2nd IEEE International Conference on Soft Robotics (RoboSoft)*, 2019, pp. 316–321.
- [21] P. Glick, S. A. Suresh, D. Ruffatto, M. Cutkosky, M. T. Tolley, and A. Parness, "A soft robotic gripper with gecko-inspired adhesive," *IEEE Robotics and Automation Letters (RAL)*, vol. 3, no. 2, pp. 903–910, 2018.
- [22] J. Hughes, U. Culha, F. Giardina, F. Guenther, A. Rosendo, and F. Iida, "Soft manipulators and grippers: a review," *Frontiers in Robotics and AI*, vol. 3, p. 69, 2016.
- [23] J. Zimmer, T. Hellebrekers, T. Asfour, C. Majidi, and O. Kroemer, "Predicting grasp success with a soft sensing skin and shape-memory actuated gripper," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2019, pp. 7120–7127.
- [24] A. Gupta, C. Eppner, S. Levine, and P. Abbeel, "Learning dexterous manipulation for a soft robotic hand from human demonstrations," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2016, pp. 3786–3793.
- [25] P. M. Khin, J. H. Low, M. H. Ang Jr, and C. H. Yeow, "Development and grasp stability estimation of sensorized soft robotic hand," *Frontiers in Robotics and AI*, vol. 8, 2021.
- [26] E. Kaiser, J. N. Kutz, and S. L. Brunton, "Data-driven approximations of dynamical systems operators for control," in *The Koopman Operator in Systems and Control*. Springer, 2020, pp. 197–234.
- [27] D. Bruder, C. D. Remy, and R. Vasudevan, "Nonlinear system identification of soft robot dynamics using koopman operator theory," in *IEEE International Conference on Robotics and Automation (ICRA)*, 2019, pp. 6244–6250.
- [28] D. A. Haggerty, M. J. Banks, P. C. Curtis, I. Mezić, and E. W. Hawkes, "Modeling, reduction, and control of a helically actuated inertial soft robotic arm via the koopman operator," *arXiv preprint arXiv:2011.07939*, 2020.
- [29] M. L. Castaño, A. Hess, G. Mamakoukas, T. Gao, T. Murphey, and X. Tan, "Control-oriented modeling of soft robotic swimmer with koopman operators," in *IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*, 2020, pp. 1679–1685.
- [30] M. Mazouchi, S. Nagesh Rao, and H. Modares, "Finite-time koopman identifier: A unified batch-online learning framework for joint learning of koopman structure and parameters," *arXiv preprint arXiv:2105.05903*, 2021.
- [31] L. Shi and K. Karydis, "Acd-edmd: Analytical construction for dictionaries of lifting functions in koopman operator-based nonlinear robotic systems," *IEEE Robotics and Automation Letters (RAL)*, vol. 7, no. 2, pp. 906–913, 2021.
- [32] B. O. Koopman, "Hamiltonian systems and transformation in hilbert space," *Proceedings of the national academy of sciences of the united states of america (PNAS)*, vol. 17, no. 5, p. 315, 1931.
- [33] M. O. Williams, I. G. Kevrekidis, and C. W. Rowley, "A data-driven approximation of the koopman operator: Extending dynamic mode decomposition," *Journal of Nonlinear Science*, vol. 25, no. 6, pp. 1307–1346, 2015.
- [34] J. L. Proctor, S. L. Brunton, and J. N. Kutz, "Generalizing koopman theory to allow for inputs and control," *SIAM Journal on Applied Dynamical Systems*, vol. 17, no. 1, pp. 909–930, 2018.
- [35] E. Kokkonis, Z. Liu, and K. Karydis, "Development of a soft robotic wearable device to assist infant reaching," *Journal of Engineering and Science in Medical Diagnostics and Therapy (JESMDT)*, vol. 3, no. 2, 2020.
- [36] R. F. Shepherd, F. Ilievski, W. Choi, S. A. Morin, A. A. Stokes, A. D. Mazzeo, X. Chen, M. Wang, and G. M. Whitesides, "Multigait soft robot," *Proceedings of the national academy of sciences*, vol. 108, no. 51, pp. 20400–20403, 2011.
- [37] K. Karydis, I. Poulakakis, J. Sun, and H. G. Tanner, "Probabilistically valid stochastic extensions of deterministic models for systems with uncertainty," *The International Journal of Robotics Research*, vol. 34, no. 10, pp. 1278–1295, 2015.
- [38] L. Shi, H. Teng, X. Kan, and K. Karydis, "A data-driven hierarchical control structure for systems with uncertainty," in *IEEE Conference on Control Technology and Applications (CCTA)*, 2020, pp. 57–63.
- [39] S. L. Brunton, J. L. Proctor, and J. N. Kutz, "Discovering governing equations from data by sparse identification of nonlinear dynamical systems," *Proceedings of the national academy of sciences (PNAS)*, vol. 113, no. 15, pp. 3932–3937, 2016.
- [40] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [41] R. Tibshirani, "Regression shrinkage and selection via the lasso," *Journal of the Royal Statistical Society: Series B (Methodological)*, vol. 58, no. 1, pp. 267–288, 1996.
- [42] D. Park, Y. Hoshi, and C. C. Kemp, "A multimodal anomaly detector for robot-assisted feeding using an lstm-based variational autoencoder," *IEEE Robotics and Automation Letters (RAL)*, vol. 3, no. 3, pp. 1544–1551, 2018.
- [43] O. M. Andrychowicz, B. Baker, M. Chociej, R. Jozefowicz, B. McGrew, J. Pachocki, A. Petron, M. Plappert, G. Powell, A. Ray, et al., "Learning dexterous in-hand manipulation," *The International Journal of Robotics Research (IJRR)*, vol. 39, no. 1, pp. 3–20, 2020.
- [44] C. Mucchiani, Z. Liu, I. Sahin, J. Dube, L. Vu, E. Kokkonis, and K. Karydis, "Closed-loop position control of a pediatric soft robotic wearable device for upper extremity assistance," in *IEEE International Conference on Robot & Human Interactive Communication (RO-MAN)*, 2022.