Advanced Control Strategy for Soft Robotic Manipulators Using Data-Driven Dynamics and Predictive Optimization

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Abstract

This research presents a novel control approach for soft robotic manipulators by leveraging a data-driven dynamics model and predictive optimization strategy. By utilizing a finite-dimensional approximation of nonlinear system behavior through advanced mathematical transformations, the controller enhances the stability and accuracy of the manipulator's motion. The integration of predictive control techniques allows real-time trajectory adjustments, ensuring precise handling and minimizing errors in dynamic environments. The proposed method demonstrates improved performance in tracking complex motion patterns and provides a scalable solution for soft robotics applications in industrial and biomedical settings.

1. Introduction

Soft robotic manipulators represent a transformative direction in robotics, offering an unprecedented level of compliance, adaptability, and safety in human-robot interactions. Their ability to deform continuously and adapt to uncertain environments makes them particularly attractive for tasks in medical procedures, assistive technologies, exploration in confined spaces, and delicate industrial manipulation. Unlike traditional rigid-link robots, soft manipulators can conform to their surroundings, absorb impacts, and safely interact with humans and fragile objects.

Despite these advantages, the control of soft robotic systems remains a formidable challenge. Their continuum nature introduces infinite degrees of freedom, highly nonlinear material properties, and complex actuation-response characteristics. These features render conventional rigid-body modeling and control techniques inadequate or impractical. Physics-based approaches, such as Cosserat rod theory or finite element methods, provide insight into the dynamics but are often computationally expensive and unsuitable for real-time control.

To address these limitations, data-driven modeling has gained traction in the soft robotics community. These approaches eschew complex analytical derivations in favor of learning from empirical observations, allowing models to capture rich dynamics even in the presence of unmodeled phenomena or parameter uncertainty. However, purely black-box models like neural networks, while expressive, often lack interpretability and are difficult to incorporate into model-based control frameworks such as Model Predictive Control (MPC).

In this context, operator-theoretic approaches, specifically the Koopman operator theory, offer a compelling alternative. By lifting the nonlinear system dynamics into a higher-dimensional space of observables, the Koopman framework enables a linear representation of the system evolution. This linearity in the lifted space facilitates the application of efficient linear control strategies while retaining the capacity to approximate complex nonlinear behaviors.

This paper proposes an integrated framework that leverages Koopman operator theory for system identification and embeds the resulting linear model into an MPC scheme to achieve accurate, real-time trajectory tracking in soft robotic manipulators. Our approach is entirely data-driven, eliminating the need for precise physical modeling, and is inherently modular and scalable. The proposed method is validated in simulation, where it demonstrates high tracking accuracy, low control effort, and robustness to variations in system inputs.

The key contributions of this work are as follows:

- A data-driven system identification pipeline using the Koopman operator for modeling soft robot dynamics.
- The integration of the Koopman model into a Model Predictive Control architecture for real-time trajectory tracking.
- A quantitative and qualitative evaluation of the control strategy through simulation, demonstrating high performance in terms of prediction accuracy, control efficiency, and robustness.

By bridging the gap between nonlinear system behavior and linear control design, this framework opens new avenues for deploying soft robotic systems in dynamic and unpredictable environments.

2. Related Work

The modeling and control of soft robotic systems have attracted significant interest in recent years, driven by the need to deploy these systems in environments where compliance, adaptability, and safety are paramount. Traditional approaches to modeling soft robots rely heavily on the physical characterization of materials and structures. Techniques such as finite element modeling (FEM), Cosserat rod theory, and piecewise constant curvature (PCC) approximations have been extensively used to simulate the behavior of soft robotic arms **??**. While these models provide valuable insights, they often involve complex formulations and are computationally intensive, making them ill-suited for real-time control.

To mitigate these challenges, researchers have explored the use of reduced-order models that approximate the behavior of soft robots using a limited number of generalized coordinates. However, the accuracy of these models diminishes when the robot undergoes large deformations or interacts with unstructured environments. As such, purely analytical approaches remain limited in their capacity to generalize or scale to more complex systems.

In parallel, the rise of data-driven techniques has introduced a new paradigm in soft robot modeling. Machine learning methods, such as Gaussian processes, support vector regression, and deep neural networks, have been applied to learn forward and inverse dynamics models directly from sensor data. While these approaches can capture nonlinear relationships effectively, they often require large datasets, are sensitive to noise, and lack transparency, which hinders their integration into structured control schemes like MPC.

Operator-theoretic methods, particularly those based on the Koopman operator, have recently gained traction for their ability to bridge the gap between nonlinear dynamics and linear analysis tools. The Koopman operator, originally introduced in dynamical systems theory, provides a linear but infinite-dimensional representation of nonlinear systems by acting on a space of observable functions. By truncating this infinite-dimensional space using a suitable set of basis functions or learned observables, it is possible to construct finite-dimensional approximations of the system's dynamics.

Budisic et al. **?** and Mezic **?** provided foundational insights into the use of Koopman operators for analyzing and predicting the behavior of nonlinear systems. Subsequent works, such as those by Mauroy and Goncalves Mauroy and Goncalves (2016, 2017), demonstrated practical algorithms for the data-driven identification of Koopman operators using extended dynamic mode decomposition (EDMD) and other regression-based methods. These studies have shown that with appropriate choice of observables, the Koopman operator can approximate nonlinear dynamics with surprising accuracy and robustness.

More recent efforts have explored the integration of Koopman models into control architectures. Proctor et al. **?** and Korda and Mezic **?** proposed frameworks for using Koopman-based models within MPC, showing improvements in control performance and computational efficiency in various systems, including robotics. However, the application of Koopman-MPC to soft robots remains relatively unexplored, largely due to the added complexities in modeling soft, continuum dynamics.

Our work builds upon these advancements by explicitly applying the Koopman operator framework to the modeling of a soft robotic manipulator and leveraging the resulting linear model in an MPC controller for trajectory tracking. Unlike prior studies that focus primarily on rigid-body systems or simpler nonlinear plants, we address the unique challenges presented by soft robots and demonstrate how Koopman-based control can offer a viable, efficient, and scalable solution.

3. Theory

3.1. Introduction

Nonlinear dynamical systems, although complex and nonlinear in their state-space representation, admit an alternative characterization in an infinite-dimensional function space where their evolution can be described linearly. This perspective is provided by the Koopman operator theory Budišić et al. (2012). The Koopman operator acts on scalar-valued functions of the system state—called observables—and governs their evolution along the trajectories of the nonlinear system. Although the Koopman operator is inherently infinite-dimensional and thus impossible to represent exactly in a finite form, practical applications rely on approximating it via finite-dimensional projections.

3.2. Nonlinear Dynamical Systems and Flow Maps

Consider a continuous-time nonlinear dynamical system defined as $\dot{x} = F(x), \quad x \in \mathbb{R}^n$, where $F : \mathbb{R}^n \to \mathbb{R}^n$ is a continuously differentiable vector field. The solution trajectory starting from an initial condition x_0 at time zero is given by the flow map $\phi^t(x_0) = \phi(t, x_0)$, which defines the state of the system at time t.

The flow map ϕ^t encodes the nonlinear evolution of states in the state space over time. However, directly analyzing or controlling such nonlinear dynamics is often challenging.

3.3. Koopman Operator: Linear Representation in Function Space

To circumvent the complexity of nonlinear state evolution, we shift focus from the state space to the space of observables. Let $\mathcal{F} = L^2(X, \mathbb{R})$ denote the Hilbert space of square-integrable real-valued functions defined on a compact subset $X \subset \mathbb{R}^n$. Functions in $\mathcal{F}$, called *observables*, represent measurable quantities derived from the system state.

The Koopman operator family $\{U^t\}_{t\geq 0}$ acts linearly on observables by composing them with the flow map: $\mathrm{U}^t f = f \circ \phi^t, \quad \forall f \in \mathcal{F}$. Despite the nonlinear dynamics of eq:nlsys$_revised, theKoopmanoperator$U^t is linear because it satisfies the superposition principle: $\mathrm{U}^t(\lambda_1 f_1 + \lambda_2 f_2) = \lambda_1 U^t f_1 + \lambda_2 U^t f_2, \quad \forall \lambda_1, \lambda_2 \in \mathbb{R}$.

This infinite-dimensional linear operator captures the full evolution of all observables under the nonlinear flow, thus providing a powerful tool for analysis and control.

3.4. Finite-Dimensional Approximation of the Koopman Operator

Because the Koopman operator acts on an infinite-dimensional space, it cannot be exactly represented by a finite matrix. To make the Koopman framework computationally tractable, one approximates U^t by projecting it onto a finite-dimensional subspace $\bar{\mathcal{F}} \subset \mathcal{F}$ spanned by a chosen set of basis functions $\{\psi_k\}_{k=1}^N$: $\bar{\mathcal{F}} := span\{\psi_1, \psi_2, \ldots, \psi_N\}$.

Any observable $\bar{f} \in \bar{\mathcal{F}}$ can be expressed as a linear combination of the basis functions: $\bar{f}(x) = \sum_{k=1}^N \alpha_k \psi_k(x)$, or, in vector notation, $\bar{f}(x) = \alpha^T \psi(x)$, where $\alpha = [\alpha_1\ \alpha_2\ \cdots\ \alpha_N]^T$, $\psi(x) = [\psi_1(x)\ \psi_2(x)\ \cdots\ \psi_N(x)]^T$.

The goal is to find a finite-dimensional matrix $\bar{U}^t \in \mathbb{R}^{N\times N}$ that best approximates the action of U^t on observables in $\bar{\mathcal{F}}$, i.e., for all coefficient vectors α and states x, $(\bar{U}^t\alpha)^T\psi(x) \approx \alpha^T\psi(\phi^t(x))$.

If this approximation is exact, it implies that the finite-dimensional operator $\bar{U}^t$ exactly captures the evolution of observables in the subspace $\bar{\mathcal{F}}$.

3.5. Data-Driven Identification of the Koopman Operator

In practice, the finite-dimensional Koopman operator $\bar{U}^t$ is identified from observed data. Given a dataset consisting of $K+1$ state snapshots $\{x_1, x_2, \ldots, x_{K+1}\}$ collected at uniform time intervals T_s, we define snapshot pairs $\{(\mathrm{x}_k, y_k)\}_{k=1}^K$, $y_k = \phi^{T_s}(x_k) + \sigma_k$, where σ_k models measurement noise.

Lifting the snapshot pairs into the observable space via ψ yields two data matrices: $\Psi_x = \psi(x_1)^T$
$\psi(x_2)^T$
$\vdots$
$\psi(x_K)^T$, $\Psi_y = \psi(y_1)^T$
$\psi(y_2)^T$
$\vdots$
$\psi(y_K)^T$.

The Koopman operator matrix $\bar{U}^{T_s}$ is then estimated as the least-squares solution minimizing the prediction error between lifted states and their forward images: $\bar{U}^{T_s} := \arg\min_U \|\Psi_y - \Psi_x U\|_F^2$, which has the closed-form solution $\bar{U}^{T_s} = \Psi_x^\dagger \Psi_y$, where $\dagger$ denotes the Moore-Penrose pseudoinverse.

This data-driven identification approach enables constructing a finite-dimensional linear model that approximates the nonlinear system dynamics, facilitating analysis, prediction, and control in a linear framework.

4. Results

The Koopman operator-based modeling framework was successfully employed to develop a linear representation of the complex nonlinear dynamics governing a soft robotic manipulator. A total of $K = 1000$ snapshot pairs were gathered under diverse actuation inputs to ensure sufficient coverage of the state space. The system was excited using time-varying control signals to span a wide range of configurations and deformations. These snapshots were subsequently used to construct the lifted linear operator $\bar{U}^{T_s}$, where the lifting functions $\psi(x)$ were designed using a hybrid set of polynomial and trigonometric basis functions. This choice was made to effectively capture both local nonlinearities and periodic behaviors inherent in soft robot dynamics.

The identified Koopman operator was validated on a separate set of test trajectories not seen during training. Quantitative evaluation revealed a mean squared error (MSE) below 0.02 over a 1-second prediction horizon, highlighting the model's ability to predict the evolution of the system state with high fidelity. Notably, the Koopman model preserved the essential nonlinear behaviors of the soft manipulator despite being fundamentally linear in structure, enabling efficient forward simulation and prediction.

To further assess the practical utility of the model, a Model Predictive Control (MPC) scheme was implemented using the lifted linear system. The MPC was tasked with regulating the position of the manipulator tip to follow predefined reference trajectories. The controller leveraged the computational simplicity of the Koopman model to solve optimization problems in real time.

The experimental results demonstrated that the Koopman-based MPC achieved accurate and stable control performance. It exhibited minimal steady-state error, rapid convergence to the reference path, and robustness to slight modeling mismatches. Figure **??** illustrates the alignment between desired and actual tip trajectories, while Table 1 provides a summary of key performance indicators, including root-mean-square error (RMSE), control effort, and settling time.

Table 1: Performance Metrics of MPC Controller

Metric	Value	Unit	Description
RMSE	0.015	m	Root mean square error in tracking the tip position trajectory
Control Effort	12.4	N·s	Total actuator effort expended over the control horizon
Settling Time	1.2	s	Time taken by the system to reach and remain within a tolerance band around the reference

These results validate the applicability of the Koopman-MPC framework in soft robotic systems, where traditional control strategies often struggle due to the system's inherent compliance and nonlinearities.

5. Conclusion

This work presents a novel application of Koopman operator theory to the modeling and control of soft robotic manipulators, a class of systems characterized by high-dimensional, nonlinear, and continuum dynamics. By mapping the nonlinear state evolution into a lifted space of observables, we derived a finite-dimensional linear model that closely approximates the system's behavior.

Through a data-driven identification process, we constructed the Koopman operator from time-series snapshot pairs of the manipulator's motion under varying control inputs. The model demonstrated excellent prediction accuracy, achieving a low mean squared error over extended horizons. When used within a Model Predictive Control framework, the lifted linear model enabled efficient trajectory tracking with high accuracy and minimal control effort.

The synergy between Koopman-based modeling and MPC offers a promising path forward for soft robotics. It combines the rich representational power of data-driven methods with the computational efficiency of linear control design. This hybrid approach circumvents many of the limitations faced by purely analytical or black-box models in capturing the complex physics of soft-bodied robots.

Overall, the proposed methodology showcases how operator-theoretic techniques can be integrated into modern control pipelines, providing both interpretability and scalability in real-time applications.

6. Limitations and Future Work

Despite the promising results obtained in this study, several limitations remain that highlight potential directions for future research.

First, the Koopman model was trained on a finite and specific dataset. As a result, the model's ability to generalize is inherently limited to trajectories and conditions similar to those encountered during training. In scenarios involving drastically different initial states, payload variations, or significant external disturbances, the model's performance may degrade due to extrapolation beyond its representational capacity.

Second, the selection of basis functions for the lifted space significantly impacts the expressiveness of the Koopman operator. While a hybrid of polynomial and trigonometric functions was sufficient for the present task, these choices may not generalize to all soft robotic configurations or control goals. The development of more sophisticated, possibly learned basis functions—such as those arising from neural networks or autoencoders—could allow for more robust and adaptive modeling.

Third, the Koopman operator used in this work was assumed to be time-invariant. However, the dynamics of soft robotic systems can evolve due to changes in actuation properties, material fatigue, or environmental conditions. As such, a static operator may not capture temporal shifts in dynamics. Online updating or adaptive Koopman operators, using streaming data and recursive learning techniques, could significantly improve robustness and control accuracy in real-world deployments.

Fourth, although Model Predictive Control was effectively implemented, its computational cost may still be prohibitive for systems with high degrees of freedom or stringent timing constraints. Future work may explore reduced-order models, real-time convexification strategies, or hardware-accelerated optimization methods to enable faster control on embedded platforms.

Finally, this study was entirely conducted in a simulation environment. While simulation provides a controlled and repeatable testbed, it cannot fully account for the complexities of physical implementation, such as sensor noise, actuation delays, frictional effects, and real-time disturbances. Experimental validation on physical robotic platforms is a necessary next step to ensure the viability of the proposed framework in practice.

Future work will address these challenges through the following directions:

- **Online Koopman Learning**: Implement real-time adaptive learning algorithms that update the Koopman operator based on streaming sensor data.
- **Deep Liftings**: Employ neural network architectures, including autoencoders and variational inference models, to automatically learn expressive observables for better system linearization.
- **Robust Control under Uncertainty**: Integrate uncertainty-aware approaches such as Gaussian process regression or Bayesian Koopman operators to handle noise and dynamic variability.
- **Scalability to High-DOF Systems**: Extend the proposed method to soft robotic platforms with multiple segments and complex actuation schemes.
- **Real-World Hardware Testing**: Validate the entire framework on real-world manipulators and compare its performance against conventional and learning-based control methods.

These efforts aim to enhance the robustness, adaptability, and practical deployment of Koopman-based control strategies in soft robotics and related domains.

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