Deformable Linear Objects Dataset and Evaluation

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***Abstract*— We present a novel dataset for real-time manipulation of deformable linear objects (DLOs), i.e., cables and hoses. This paper introduces a framework for configuration estimation and learning DLO dynamics. This dataset aims to disambiguate DLO dynamics from all other factors. Moreover, we introduce**

***Index Terms*—**

I. Introduction

This work aims to develop a novel method for configuration estimation and tracking deformable linear objects (DLOs) by enforcing dynamics constraints. Moreover, we will introduce a new active vision dataset dedicated to manipulating various free-hanging DLOs to highlight their dynamics. Our dataset will contain RGBD frames, robot state stream, and dynamic test inputs. Additionally, we will test and evaluate multiple DLOs with various attributes. We will discuss how robustly we can track the configuration of each DLO in test cases.

In recent years, active control of deformable objects has become a topic of interest among researchers, with applications in various industries, e.g., surgical robotics, food handling, and manufacturing [1]. Active control of deformable objects remains particularly challenging, as they exhibit strongly nonlinear dynamics when subject to external forces. Deformable objects are divided into three main categories, 1D or deformable linear objects, e.g., rope and cable; 2d or deformable planar objects, e.g., paper and cloth; and deformable volumetric objects, e.g., pillow and sponge. To be more precise, we are interested in active vision applications that involve real-time configuration control of deformable linear objects or DLOs.

Researchers have introduced various methods to address both the perception and control tasks in applications that involve active control of DLOs, [2, 3, 4, 5]. However, the robust perception DLOs remains an open challenge for manipulation tasks. The observed shapes often suffer from false holes, missing parts, no detection in large sections, or inconsistent tracking between frames. [6] introduced a method for tracking deformable objects under partial occlusion by using geometric constraints. This work aims to incorporate dynamic constraints, introduce a dynamic test set, and expand the application to more DLOs.

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II. Related Work

In recent years, manipulation and sensing of deformable objects have become a topic of interest among researchers, with applications in various industries, e.g., surgical robotics, food handling, and manufacturing [1]. Robotic manipulation of deformable objects remains particularly challenging, as they exhibit strongly nonlinear dynamics when subject to external forces. Although researchers have successfully introduced various learning-based methods for manipulating DLOs, manipulating deformable objects has remained mostly manual, causing industrial and economic bottlenecks.

However, a new paradigm is emerging from data analysis and fluid dynamics research; data-driven modeling offers superior techniques for extracting explicit low-rank representations of complex systems from high-dimensional measurements [7, 8]. This proposal uses state-of-the-art data-driven modeling techniques to consider a framework for system identification, configuration estimation, and control of Kirchhoff elastic rods or DLOs, e.g., cables and ropes. Physics-informed dynamic mode decomposition (piDMD) and Koopman operator theory provide a promising theoretical foundation in support of model predictive control (MPC) of DLOs [9, 10].

In [3], the authors formulated the problem as a fully observable Markov decision process and deployed a learning-based approach. They introduced the Canonical Visual Forward model (CaVFM), a sample efficient method for learning DLO manipulation tasks. They leverage fully-connected neural networks to preserve and learn the spatial structure of the target object.

They used self-supervised data collection and a real robot to obtain their data on 1000 manipulation episodes. In CaVFM, the authors introduce a vision-based framework for predicting and manipulating DLOs, which requires far fewer samples to train than other approaches with comparative performance. They leverage fully-convolutional networks (FCNs) to preserve spatial information throughout training and represent inputs canonically. They pair object observation and displacement images at the input stage before feeding them to an FCN; this preserves the spatial information of both object and displacement images (translates to action input) throughout training. This is the main factor this approach performs comparatively well with only 1000 training samples. They leverage a pick-and-place robotic model for its visual input space and action output space framework as they expand their capabilities to DLO manipulation.

Various approaches have been introduced for the quasi-static manipulation of DLOs, limiting manipulation tasks to low-speed movements. Bretl and McCarthy introduced a sampling-based path-planning method for dual-arm DLO manipulation tasks where grippers hold the object at both ends. They showed that a DLO in static equilibrium is a local solution to a geometric optimal control problem, the position and orientation of grippers dictate the boundary conditions. Using optimal control on manifolds and Lie-Poisson reduction, they prove that the set of all equilibrium is a smooth manifold of finite dimensions. They analytically proved that DLO dynamics is a smooth left-invariant Hamiltonian system in a dual-arm configuration that can be represented explicitly in 6 dimensions using a dual-basis functions approach [11]. Although such dimensionality reduction of DLO dynamics is remarkable, this approach is strictly limited to dual-arm configuration and slow-speed motions. Furthermore, different DLOs exhibit various degrees of elastoplasticity over different intrinsic dimensions; a systematic approach for extracting the intrinsic coherent structures from observations would offer better generalization to other DLO as it eliminates cumbersome analytical derivations. This proposal seeks a more general and systematic approach for obtaining the rank and the basis functions that are the best linear approximation of the data.

Many learning-based methods operate under a similar quasi-static assumption; they learn a discrete state-action mapping to find the optimal sequence of actions, given an initial condition and a goal state. Zhang used an auto-encoder-decoder architecture to map nonlinear states and actions to their corresponding linear latent spaces. Then, they trained a linear dynamic model in the latent space to learn the mapping between [or the latent state prior?], the latent prior state, the latent action, and the latent posterior state [8]. Although this method learns a linear operator in the latent space that successfully predicts up to 10 future states, the dynamic mapping is purely statistical, locally linear, and heavily dependent on the provided training set. Even though autoencoders are a powerful tool for dimensionality reduction, they encode input data to a specified rank and only use a polynomial basis function.

There are other deep learning methods for dual-arm and free-end DLO manipulation tasks that leverage a variety of techniques, e.g., movement primitives, model-free reinforcement learning, contrastive learning, and dense object descriptor, but they all have similar limitations.

e.g. learning-based models [12], finite element models, and latent space models [13].

Various methods have been proposed for modeling or learning state dynamics of deformable objects [14, 13, 15, 16, 17]. However, existing methods suffer from a range of issues that make them impractical for deployment in a real-time and highly dynamic environment. These issues are attributed to the nonlinear nature of DLO dynamics and the high computational cost associated with real-time perception, high-dimensional representation, and model uncertainty mitigation techniques.

III. Background

In this paper, we will introduce a new augmented dataset for... The dataset is based on a previously available work [13] where we added annotation that allows for more efficient learning of the DLO dynamics. Moreover, unlike [13] and [14] who used VEA and online-offline Adaptive Control for configuration estimation, respectively; we deploy *the Koopman Operator* to learn the underlying *locally linear dynamics* of the subject DLO.

IV. Method

A. Setup

Something.

B. Model

We define an approximate observation function for our Koopman operator as

$$y_k = g(x_k) \equiv \Psi(x_k), \tag{1}$$

where $\Psi(x_k)$ is a vector-valued function

$$\Psi(x_k) = [\psi_1(x),\ \psi_2(x), ...,\ \psi_N(x)]. \tag{2}$$

V. Evaluation

A. Experiments

Something.

B. Manipulation Task Experiments

Something.

VI. Conclusion and Future Work

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