DLO-RoboMan: Dataset and Dynamic Test for Robotic Manipulation of Deformable Linear Objects

Bardia Mojra, William J. Beksi, and Nicholas R. Gans

***Abstract*— We present a novel dynamic data generation framework for the robotic manipulation of deformable linear objects (DLOs), i.e. cables and wires, in a free-hanging configuration. Our data generation framework systematically explores the performance surface that governs the object dynamics by testing a balanced distribution of input trajectories. Our goal is to reduce the computational load for data-driven methods by collecting better dynamic data, data that is rich with dynamic information. To further highlight the object's intrinsic dynamics, we avoid contacting other surfaces to reduce external and unwanted interference. Moreover, we present a 3D dataset generated by the mentioned framework where we test four distinct DLOs and compare their output states and internal dynamics. This framework features an automatic annotation system for the generated point cloud that further streamlines data-driven learning for individual DLO without any prior knowledge.**

***Index Terms*— Deformable linear objects, dynamic dataset, manipulation**

I. Introduction

In recent years, the manipulation 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]. However, active control of deformable objects remains particularly challenging; they exhibit strong nonlinear dynamics when subjected to external forces and are particularly sensitive to initial conditions. Researchers have introduced numerous methods addressing both the perception and control tasks in applications that involve active control of DLOs, [2, 3, 4]. However, the robust estimation and control of DLOs remain an open challenge in industrial settings. Existing models do not generalize well to unknown DLOs, tasks with different initial conditions, end-goal configurations, and input speeds for the arm. Moreover, existing methods require expert mathematical modeling of object geometry, time-consuming data annotation, and costly computation for individual objects and tasks.

For simplicity, in this work, we focus on manipulating deformable linear objects in free-hanging configurations. More precisely, with our dataset and dynamic testing framework for DLOs, we aim to inspire the research community to develop solutions for the real-time manipulation of DLOs without prior knowledge. To achieve this, we developed a dynamic test procedure for DLOs in a free-handing configuration that explores the object's intrinsic dynamics performance surface.

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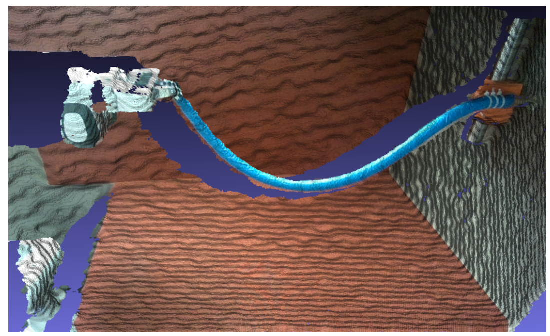

Fig. 1. Raw dataset mesh.

We build on the assumption that a DLO in a dual-arm configuration is governed by low-dimension closed-loop control laws [5]. Thus, we developed a series of robotic tests for learning the intrinsic dynamics of individual DLOs. The test set is a free-hanging DLO with one end secured to a pole and the other grasped by a robotic arm, effectively removing contact dynamics and surface friction of DLO with other objects.

In summary, our contributions include the following:

- We introduce a dynamic dataset, DLO-RoboMan, for learning the object's intrinsic dynamics in applications for the robotic manipulation of DLO.
- We present a framework for generating and annotating training data for learning DLO dynamics in tied-end robotic manipulation applications.
- We evaluate multiple DLOs with our framework and compare the results with existing methods.

The remainder of this paper is organized as follows. We review related literature in the related work section II. Setup section, III, provides further details on the data collection setup, test subjects, data acquisition software setup, and system calibration. Next is the method section, IV, where we discuss the proposed dynamic test framework, initial conditions, data collection, and the test procedure. In the dataset section, V, we discuss dataset file structure, post-processing, annotation framework, and limitations. In the last section, VI, we conclude by discussing the limitations of our work and our recommendation for future work.

II. Related Work

Robotic manipulation of deformable linear objects has attracted significant attention in recent years due to its applications in both domestic and industrial settings. A survey by Sanchez et al. highlights the importance of this field, discussing the challenges and opportunities for robotics in manipulating deformable objects [1]. This section categorizes the related work into three groups: learning-based, model-based, and hybrid methods. These approaches leverage techniques such as deep learning, reinforcement learning, autoencoder-based methods, physics-based modeling, and simulation to effectively manipulate deformable linear objects. These methods provide exciting avenues for future research and development in the field of robotics and automation.

A. *Learning-Based Methods*

Learning-based methods employ machine learning techniques to learn the complex relationships between inputs and outputs. Deep learning has been widely used in this category, as shown in works such as Laezza et al., where deep neural networks were used to predict the future states of the object and plan optimal trajectories accordingly [6]. Reinforcement learning has also been applied to manipulate deformable linear objects; Wang et al. formulated the problem as a Markov decision process and learned a policy using reinforcement learning [4]. Acker et al. learned a data-driven low dimensional model to estimate the object's contact state transition with a flat surface [7]. Additionally, autoencoder-based methods have been used to train a latent space dynamic model with robust center-line extraction, as demonstrated by Qi et al. [8].

B. *Model-Based Methods*

On the other hand, model-based methods utilize physics-based models to simulate and control the object's deformation. Zurn et al. proposed a method that used point cloud data to generate a kinematic model of the deformable linear object [9]. Simulation-based methods have also been used to train the controllers of deformable linear objects. Bretl et al. developed an explicit low-dimensional model for DLO state dynamics in dual-arm configuration [5].

C. *Hybrid Methods*

As the name suggests, hybrid methods combine the strengths of both learning-based and model-based methods. Yu et al. used a hybrid method to learn a global model of the deformable linear object and used the model to plan and control the manipulation of the object [3]. Laezza et at. developed ReForm: A Robot Learning Sandbox for Deformable Linear Object Manipulation, a hybrid method that combines physics-based simulation with machine learning to train the controller of the deformable linear object [10].

In summary, the recent literature on robotic manipulation of deformable linear objects can be categorized into learning-based, model-based, and hybrid methods. These approaches leverage techniques such as deep learning, reinforcement learning, autoencoder-based methods, physics-based modeling, and simulation to effectively manipulate deformable linear objects. These methods provide exciting avenues for future research and development in the field of robotics and automation.

III. Setup

The setup consists of a robotic arm, depth camera, test rig, scientific pole, DLO mount, and the test DLO. We tried to keep the setup simple and straightforward to make our approach more reproducible. For the robotic arm, we used a Franka Emika Panda arm which is installed off the rig and for perception, we used an Intel RealSense D435i depth camera.

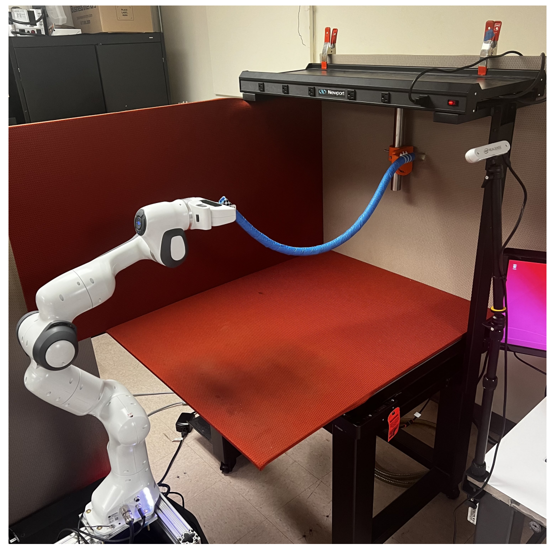

Fig. 2. DLO data collection setup.

The rest of this section is organized as follows. Section III-A provides further details on the physical attributes of the experiment workspace, DLO mount, robotic arm, and depth camera. Section III-B briefly describes test subjects and their physical attributes. Section III-C provides details of software tools we used for collecting data. Section III-D provides a brief overview calibration procedure we used in this work.

A. *Physical Setup*

The physical setup consists of a shock-absorbent scientific table with an overhead section. We have added textured fabric pads to three sides of the table to create a semi-open experiment workspace. We chose textured red cloth pads for the bottom and adjacent planes because it reflects light more evenly, and the high contrast with DLOs allows for automatic annotation of RGB point cloud data. The workspace is 58 inches deep, 40 inches wide, and 32 inches tall. We have installed a scientific pole upside-down under the overhead. The pole is installed at the back and is centered. Moreover, we designed and printed a PLA mount for the DLOs with angular DoF that is installed on the pole. We release the CAD file with the dataset to encourage review and broader use of our work. We aim to deploy a robotic arm to perform manipulation tasks so that we can record the trajectories and robot state. Robot control input, state, and applied torque are important for learning the true intrinsic dynamics of objects. Unfortunately, we could not include them in this experiment due to various technical difficulties with UR5e and Panda robotic arm. We performed the experiments manually to meet this submission's deadline. We used an Intel RealSense D435i stereo vision depth camera and collected the data at the highest resolution settings of 480 by 848 pixels at 30 Hz. As a measure of good practice, we tune camera presets for each test series and save it as "rs_presets .json" under its corresponding data series directory.

B. Test Subjects

A total of four DLOs were used as test subjects. From the left, first is "blue hose," or DLO 01, a steel-reinforced hose wrapped in blue masking tape. The hose is transparent and reflects light unevenly in its original form, so we wrapped it in blue masking tape. Next is "bundled three," which is three cables bundled together at three points with zip ties; the red and back are 8 AWG shredded wires, and the blue is a CAT6 Ethernet cable. Next is the "3-conductor" cable, which is made of three 12 AWG conductors wrapped in black plastic insulator. Last is "yellow wire," which is a 16 AWG shredded wire. For more information on DLO specifications, refer to "dlo_specs . txt" file in the corresponding directory within the dataset. Due to a lack of time, we have been able to collect data with only one cable.

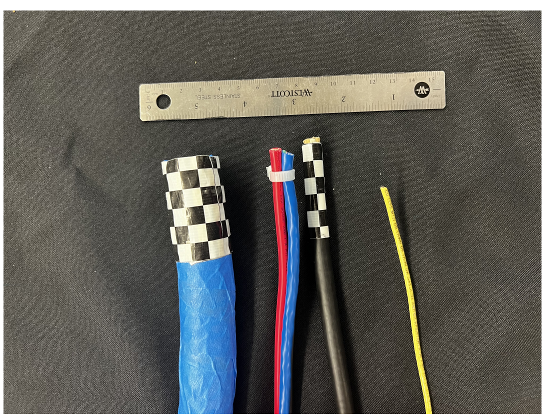

Fig. 3. Deformable linear objects.

C. Software Setup

The source code is written in Python

D. Calibration

We perform camera calibration using the RealSense camera calibration ROS package to ensure we are collecting accurate and reliable data. For more information, follow RealSense calibration ROS package documentation. Due to a lack of time, we resorted to skipping this step to meet the deadline for this submission.

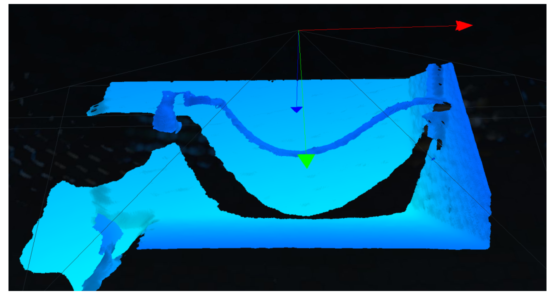

Fig. 4. Object mesh.

IV. Method

We developed our dynamic tests

A. Dynamic Tests

Table IV-A outlines five dynamic tests we designed to capture the intrinsic dynamic of DLOs.

Test	Description
1	Static
2	Linear X-Axis
3	Linear Y-Axis
4	Linear Z-Axis
5	Sinusoidal X-Axis
6	Sinusoidal Y-Axis
7	Sinusoidal Z-Axis

B. Initial Conditions

C. Data Collection

D. Test Procedure

V. Dataset

This dataset aims to enable robotic manipulation and control of DLOs by exploiting their dynamic constraints. We particularly want to extract data points representing pure object dynamics from RGBD frames.

A. File structure

B. Post-Processing

C. Initial Conditions

D. Annotation Framework

E. Limitations

VI. Conclusion and Future Work

References

[1] J. Sanchez, J.-A. Corrales, B.-C. Bouzgarrou, and Y. Mezouar, "Robotic manipulation and sensing of deformable objects in domestic and industrial applications: a survey," *The International Journal of Robotics Research*, vol. 37, no. 7, pp. 688–716, 2018.

[2] R. Lee, M. Hamaya, T. Murooka, Y. Ijiri, and P. Corke, "Sample-efficient learning of deformable linear object manipulation in the real world through self-supervision," *IEEE Robotics and Automation Letters*, vol. 7, no. 1, pp. 573–580, 2021.

[3] M. Yu, K. Lv, H. Zhong, S. Song, and X. Li, "Global model learning for large deformation control of elastic deformable linear objects: An efficient and adaptive approach," *IEEE Transactions on Robotics*, 2022.

[4] Y. Yang, J. A. Stork, and T. Stoyanov, "Online model learning for shape control of deformable linear objects," in *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2022, pp. 4056–4062.

[5] T. Bretl and Z. McCarthy, "Quasi-static manipulation of a kirchhoff elastic rod based on a geometric analysis of equilibrium configurations," *The International Journal of Robotics Research*, vol. 33, no. 1, pp. 48–68, 2014.

[6] R. Laezza and Y. Karayiannidis, "Learning shape control of elastoplastic deformable linear objects," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 4438–4444.

[7] J. Acker and D. Henrich, "Manipulating deformable linear objects: characteristic features for vision-based detection of contact state transitions," in *Proceedings of the IEEE International Symposium onAssembly and Task Planning, 2003.* IEEE, 2003, pp. 204–209.

[8] J. Qi, G. Ma, P. Zhou, H. Zhang, Y. Lyu, and D. Navarro-Alarcon, "Towards latent space based manipulation of elastic rods using autoencoder models and robust centerline extractions," *Advanced Robotics*, vol. 36, no. 3, pp. 101–115, 2022.

[9] M. Zürn, M. Wnuk, C. Hinze, A. Lechler, A. Verl, and W. Xu, "Kinematic trajectory following control for constrained deformable linear objects," in *2021 IEEE 17th International Conference on Automation Science and Engineering (CASE)*. IEEE, 2021, pp. 1701–1707.

[10] R. Laezza, R. Gieselmann, F. T. Pokorny, and Y. Karayiannidis, "Reform: A robot learning sandbox for deformable linear object manipulation," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 4717–4723.