Deformable Linear Objects: Dataset and Evaluation

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***Abstract*— In this paper, we will introduce a new augmented dataset for learning DLO local dynamics. The dataset is based on a previously available work [1] where we added annotation that allows for more efficient learning of the DLO dynamics. Moreover, unlike [1] and [2] 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. [1] is the main paper I am following as for base example. [2], [1], and [3] are the main papers I am following. Each of those papers have the code available for them. [2] provides the code for a reinforcement learning data collection setup with Unity and UR5. This is great basis for my follow up work. [?] is the paper I mentioned at the meeting. This paper is by Levine's group and I think both dataset and learning method are very bad. Dr. Gans agreed. The rope is not dynamic for the most part. The test setup does not challenge or interact with object dynamics and its configuration is mostly determined by contact friction with the table. Moreover, the learing methods is extremely inefficient because most pixels in 60K images contain no information regarding object dynamics. My goal is to learn dynamics with the Koopman Operator only from regions where we observe a bend on the DLO. Everything else is noise in regards to the dynamics. I need to read on the Koopman Operator.**

***Index Terms*—**

I. Introduction

In summary, our contributions are the following.

- new tasks
- novel data generation framework
- Novel RL framework
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Our source code and dataset are available at [].

The remainder of this paper is organized as follows. Relevant related literature is discussed in Section II. Our approach for ... is presented in Section III. The design and results of our experiments are demonstrated and explained in Section IV. In Section V, the paper is concluded and future work is discussed.

II. Related Work

DLO manipulation applications:

Review by Sanchez et al [ICRA21-002-15]

Real time manipulation of DLOs is a multi-faceted problem and it can be divided to the following parts, 1) learning the DLO dynamics, 2) representing it in a computationally efficient manner that would allow for real-time manipulation, 3) and controlling it to reach target configuration.

end to end deep learning approaches:

End-to-end approaches are prone to catastrophic failure and are costly to train in terms of time and computation.

On DLO prepresentation approaches: - Learning based representation: - Model based representation:

Deformable linear object prediction using locally linear latent dynamics: [1]

DLO representation: quasi-static and non-quasi-static representations

manipulation of DLOs with quasi-static: learning based controller:

model based estimator and controllers:

manipulation of DLOs with non-quasi-static representation: [3] - more feasible for high speed applications - Movement primitives - a series of open loop control input commands

III. Method

IV. Experimental Evaluation

V. Conclusion and Future Work

References

[1] W. Zhang, K. Schmeckpeper, P. Chaudhari, and K. Daniilidis, "Deformable linear object prediction using locally linear latent dynamics," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 13 503–13 509.

[2] M. Yu, H. Zhong, and X. Li, "Shape control of deformable linear objects with offline and online learning of local linear deformation models," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 1337–1343.

[3] H. Zhang, J. Ichnowski, D. Seita, J. Wang, H. Huang, and K. Goldberg, "Robots of the lost arc: Self-supervised learning to dynamically manipulate fixed-endpoint cables," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 4560–4567.

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