Progress Report

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1 Specific Research Goals

- VPQEKF (—): Work on the paper.
- DLO Manipulation Dataset (ICRA - Sept. 1st)

2 To Do

- QEKF Paper - 30% extension (—): lack of direction
- Implementation (—):
  - Noise issue: noise cannot be modeled - revisit
  - SfM: RQuEst cannot find solution – under investigation
- DLO Manipulation: (ICRA - Sept. 1st)
  - Work on the paper everyday – up-coming
  - ICRA 2022 RL workshops: gym, stable-baseline3, and RL zoo – on-going
  - Setup digital twin reinforcement learing setup:
    - Unity Robotics extension setup – on-going.
    - Design dynamic DLO data collection system.
    - Build work cell. – on-going
    - Collect data and create a dataset.
    - Define evaluation metrics.
    - Create a high frequency RGBD dataset with UV-frames and open-loop input control actions as the ground truth.
  - Real-Time Preception
    - Deep learning methods for keypoint pose estimation in real-time.
    - Use UV dye dataset
    - Use PVNet-like approach for known-object pose estimation.
  - Learning DLO Dynamics and System Identification
    - List feasible approached for learing DLO dynamics
    - Model dynamics and deformity in a latent space
  - Real-Time Control

* Time model inference, using auto-encoders generate the lowest dimensional representation for each object.
* Use another GAN model for object deformity for each object.
* Evaluate encoded representation for accuracy.
* Used another GAN to explore other abstraced representations from individual encoded representation. In theory, we can create a low dimensionsal representation for multiple similar objects, given all individual low-dimensional representations. This is inspired by "fundamental principles first" approach which has universal applicability.

3 Progress

The following items are listed in the order of priority:

- XEst (RAL —): No technical update. Dr. Gans, Asif, and I met to discuss Asif's involvement. He didn't seem interested. Kaveh's work is incomplete, I shared this Dr. Gans he agreed. I will finish it later, I will have to obsess over it. This is where I shine the most.

- DLO State Estimation (ICRA - Sept. 1st): 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. [4] 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.

- Maicol (REU): I want him to continue on ROS2 and Unity and recreate [2] over the summer. I will help him.
- PyTorch Tutorials: Transfer learning.
- Omniverse: Apply for access. – To-Do

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)*, pp. 13503–13509, IEEE, 2021.

[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)*, pp. 1337–1343, IEEE, 2022.

[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)*, pp. 4560–4567, IEEE, 2021.

[4] A. Nair, D. Chen, P. Agrawal, P. Isola, P. Abbeel, J. Malik, and S. Levine, "Combining self-supervised learning and imitation for vision-based rope manipulation," in *2017 IEEE international conference on robotics and automation (ICRA)*, pp. 2146–2153, IEEE, 2017.