Progress Report

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1 Research Plan

This section outlines my current research plan where the main ideas, target conference/journal, and expected date of completion for each paper are provided. Target conferences: ICRA, IROS (March), CASE (Late Feb.), NIPS. Target Journals: RAL, CVPR, CORAL.

- Koopman-01 (IROS - Dec. 1st - active): Koopman-based MPC control of VTOL-DIP and VTOL-TIP in simulation, DLO pose estimation in simulation, experiments on choice of basis function and lifting dimensions, and performance comparison with optimal, robust, and/or adaptive control schemes.
- Koopman-02 (ACC - Sep 30th - active): A review on Koopman-based control schemes. Not enough, make it part of another paper. Read papers and write literature reviews.
- Koopman-03 (RAL - Mar. 1st - status): Extension to Koopman-01, Koopman-based dynamic estimation of DLO, collect dynamic DLO dataset, prediction of DLO configuration.
- Quest-01 (IROS - Mar. 1st - next): Optimal transform solution for QuEst based on dominant mode decomposition (DMD).
- Quest-02 (IROS/RAL - date - status): QuEst-based EKF, structure from motion, and VSLAM, compare performance with existing methods.
- Koopman-04 (IROS/RAL - date - status): Physics Informed (PI) Koopman-based control of a DLO, show obtained is persistant, compare to other non-PI methods, offline-online learning.
- Koopman-05 (IROS/RAL - date - status): PI Koopman operator (PIKO) based persistant model for DLOs, low dimensional, compare performance, offline-online learing/adapting, fast transfer learning.
- Koopman-06 (IROS/RAL - date - status): PIKO-based unit segment model for DLOs, more generalized, should yield better performance if number segments are selected online in order to obtain optimal representation in real-time given available hardware, compare results.
- Koopman-07 (IROS/RAL - date - status): DLO dataset, PIKO-based reinforcement learning of real DLO dynamics in a digital twin (DT)

setting, experiments of model persistance, compare learning rate with neural network based methods, compare performance with available methods, and experiments on learing limitations.

- Koopman-08 (IROS/RAL - date - status): Koopman-based real-time control of DLO on GPU.
- Koopman-09 (IROS/RAL - date - status): PIKO-based real-time control of DLO on GPU.
- Koopman-10 (IROS/RAL - date - status): PIKO-based real-time control of deformable planar objects (DPO).
- Koopman-11 (IROS/RAL - date - status): PIKO-based real-time control of deformable volume objects (DVO).
- Koopman-12 (IROS/RAL - date - status): PIKO-based unit segment for DPOs, on GPU.
- Koopman-13 (IROS/RAL - date - status): PIKO-based unit segment for DVOs, on GPU.

2 To Do

- QEKF Paper (On pause):
  - Noise issue: noise cannot be modeled - DMD is a robust noise on high dimensional orthonormal time series and should be able to denoise QuEst solutions.
  - SfM: RQuEst cannot find solution - A potential solution is described briefly above.
- DLO Manipulation: (ICRA - section out of date)
  - Setup digital twin reinforcement learing setup:
    - Unity Robotics extension setup – done.
    - Design dynamic DLO data collection system.
    - Build work cell. – done
    - 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 – on hold
- Learning DLO Dynamics and System Identification - PIKO - Ongoing

3 Progress

The following items are listed in the order of priority:

- DLO Manipulation (IROS): Last week, I looked into SimScape code API so it can be integrated into our code. It has a learning curve that could delay our progress. Dr. Gans and I decided to set that aside in the interest of implementing and experimenting with a cart-pendulum system. I implemented the model and associated Koopman operator controller. The model is a classical explicit dynamical expression. However, the controller is different. In their seminal work the authors, Ian Abraham and Tod Murphy, define two mapping functions for state and input, respectively. The state, $x(t)->z(x(t))$ is lifted from 4 to 7. Then, they consider an observable function $x(t), u(t)->v(x(t), u(t))$, and provided its derivatives dv/du and dv/dz. They define a *general objective function* with a *differentiable policy*. They use a technique called *mode insertion gradient* which, I do not understand at this time. This is too advanced and I only stared reading this part on Friday, so I do not fully understand it. They analytically derive a *Control Hamiltonian with the input integrated*. This allows for optimal control with the input and significantly reduced the training time. Moreover, they extend this with an active learner which, I have not looked into. *Active-Koopman* is a separate paper [1] from [2] which, we were originally following but the explanation did not make sense for the cart-pendulum example. I ported the code in and I am stepping through it. I don't believe the code I ported in was the active learning example because they provide a separate example for that but I am not sure. In the code, the policy is actively updated.

- Maicol (REU): I want him to start working on Omniverse and Isaac Sim tutorials, at his leasure. I believe having someone on the team who is familiar with these development environments brings considerable value to the team and particularly my own research.

- DoD SMART (Dec 1st.): I started the application.

- XEst (RAL —): No update.

References

[1] I. Abraham and T. D. Murphey, “Active learning of dynamics for data-driven control using koopman operators,” *IEEE Transactions on Robotics*, vol. 35, no. 5, pp. 1071–1083, 2019.

[2] I. Abraham, G. De La Torre, and T. D. Murphey, “Model-based control using koopman operators,” *arXiv preprint arXiv:1709.01568*, 2017.