Progress Report

Bardia Mojra

October 23, 2022

Robotic Vision Lab

The University of Texas at Arlington

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:

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

- DLO Manipulation (IROS): This week, Dr. Gans and I debugged MPC-Koopman Cart-Pendulum code and I was able to run some tests. For now, I ran 5 simple tests where they all have the same training configuration but the tests are run for different lengths. The goal of this preliminary experiment is to examine controller stability of at steady state. The original code used 10 sets, 200 samples each for training and 200 samples for test run duration. I kept the same training congfiguration and increased test run samples from 200 to a range from 500 to 100,000 samples. Figure 1 depicts lifted state variables and control input for T000002 with 1000 test run samples. I observed a mild oscillation about the upright position but it is more stable at steady state than an optimal controller. This is very interesting. Compared to an optimal controller, MPC-Koopman controller damps state error much less aggressively but it is UUB stable for much longer. Figure 2 depicts the system lifted state and control input for T000004 with 20,000 test run sample. An optimal controller, exhibits random jerky response that makes the system eventually become unstable. I will review the results with Dr. Gans, work on DOD Smart proposal and move on to the dataset [1].

- Maicol (REU): No update.

- XEst (RAL —): No update.

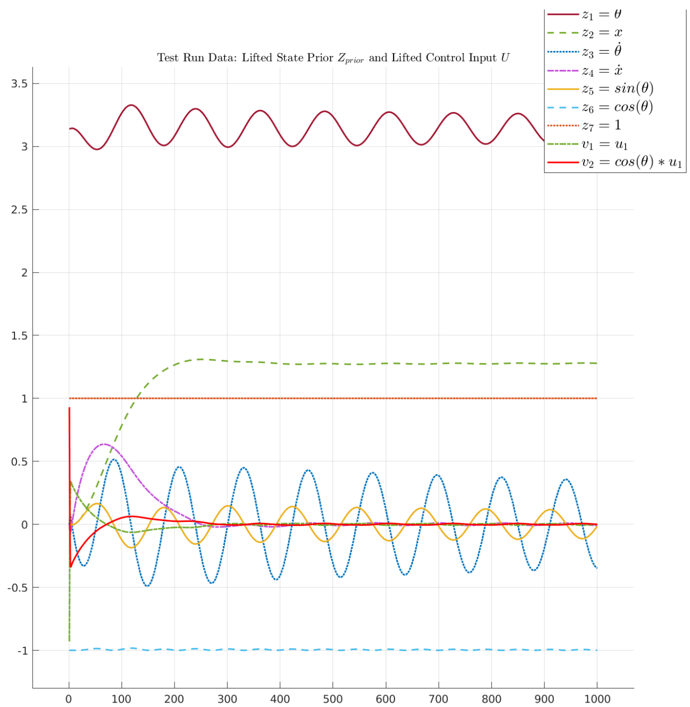

Figure 1: Inverted pendulum test run data with $nSamps = 1000$.

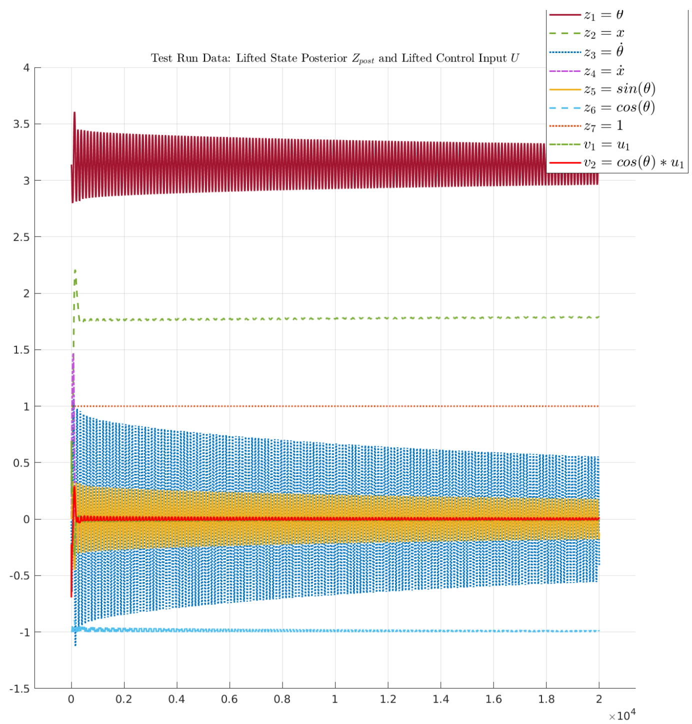

Figure 2: This image depicts the lifted state prior variables $z(x)$ and the lifted control variables $v(u)$ at steady state.

References

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