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:

- DOD Smart: I need to work on this asap.

- DLO Manipulation (IROS): Last week, I was mostly busy with assignments and exams. I was able to implement MPC-Koopman controller for an inverted pendulum system. For training purposes, I am able to generate *nTrials* test runs with a length of *nSamps* given generated random input and initial conditions. Moreover, lifted state and control input variables are depicted in figures 2 and 3. This inverted pendulum example is based on python implementation for [1].

- Maicol (REU): No update.

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

- XEst (RAL —): No update.

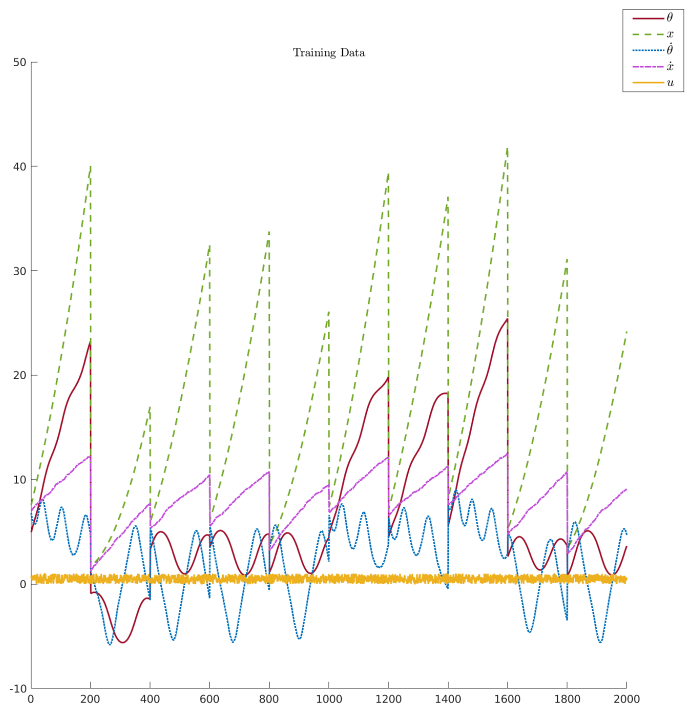

Figure 1: Inverted pendulum training data with $nTrials = 10$ and $nSamps = 200$. The data is generated with random initial conditions and random input. Plot shows system state and control input with the following as its variables, pendulum angle θ, cart position x, pendulum angular velocity $\dot{\theta}$, cart velocity $\dot{x}$, and control input u.

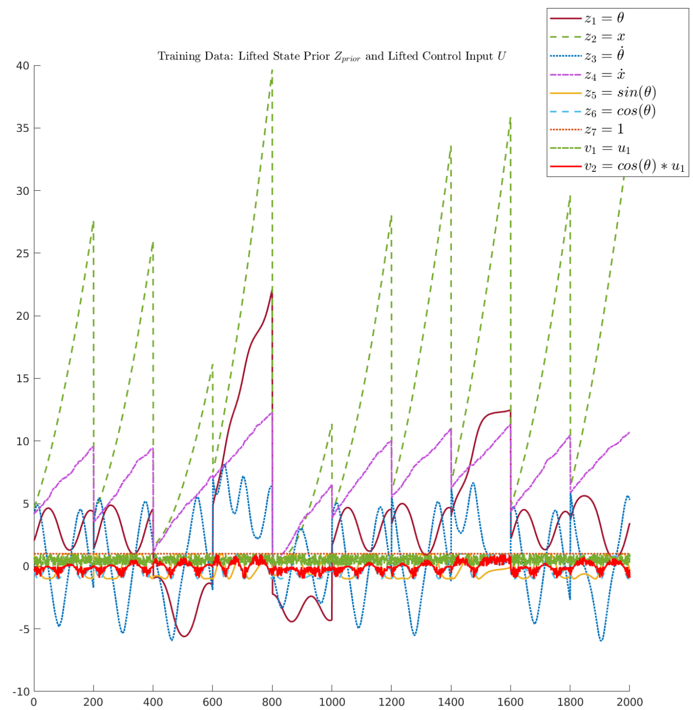

Figure 2: This image depicts the lifted state prior variables $z(x)$ and the lifted control variables $v(u)$.

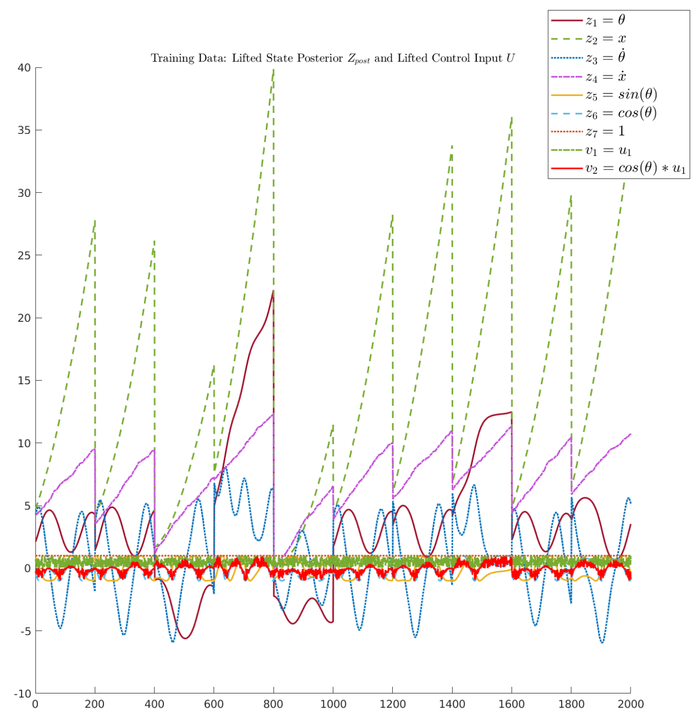

Figure 3: This image depicts the lifted state posterior variables $z(x)$ and the lifted control variables $v(u)$.

References

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