Nonlinear Inverse Optimal control for human motion prediction

Keywords. **Koopman Operator theory, Inverse optimal control, Data-driven techniques, Machine learning**

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Research Problem Statement. Collaboration between humans and robots is becoming increasingly prevalent in today's society, wherein the precision, speed, and task repeatability of robotic systems are complemented by the adaptability, ingenuity, and context-aware decision making capabilities of humans to achieve common objectives. This collaboration extends well beyond industrial settings into fields such as healthcare, manufacturing, education, and even daily domestic activities.

While robotic agents can share task specific information directly among one another, the intentions of the human collaborators in the shared workspace often need to be inferred based on observations of their motions. In this project, we are interested in developing data-driven algorithms towards estimating control objectives of human collaborators from optimal demonstrations, with or without the knowledge of dynamic model of the human agents.

Towards this goal, we aim build upon topics related (but not limited) to nonlinear optimal control theory, machine learning, and optimization, to investigate well-posedness of the inverse problem. One idea is to utilize Koopman-based surrogate linear models for the unknown system dynamics, followed by inverse LQR in the Koopman space. This idea has only been partially explored so far [1]. Finally, we are also interested in comparing our techniques against other competing approaches, for example, imitation learning, wherein one aims to predict motion by directly learning the control policies of the human from trajectory demonstrations [2][3].

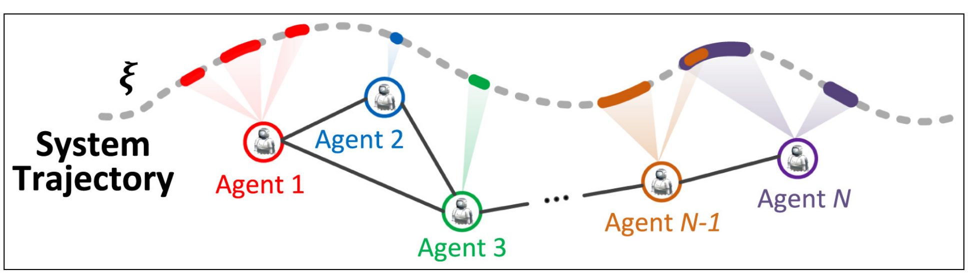

Figure 1: Setup of learning from demonstration, wherein trajectories from optimal demonstrations are available (possibly in segmented pieces [3]). The goal is the learn what objective function does this trajectory optimize, and then use this learnt objective function for motion prediction.

Expected workload: If you would like to contribute to this topic, your work will include

1. Getting familiar with literature on trajectory optimization, inverse optimal control, learning from demonstration, system identification.
2. Utilize Pontryagin's principle in combination with Koopman linear representation to develop frameworks to estimate cost functions from optimal demonstrations.
3. Code implementation and application of the developed framework for motion prediction in human-multirobot settings.

Prerequisite: Good knowledge on control theory, machine learning, and optimisation; Working proficiency with Python and Matlab, basic experience with PyTorch, strong motivation to perform hands-on experiments is a plus.

Type of work: 50% theory, 50% implementation.

References

[1] Z. Liang, W. Hao, and S. Mou, "A data-driven approach for inverse optimal control," in *2023 62nd IEEE Conference on Decision and Control (CDC)*, pp. 3632–3637, IEEE, 2023.

[2] W. Jin, T. D. Murphey, D. Kulić, N. Ezer, and S. Mou, "Learning from sparse demonstrations," *IEEE Transactions on Robotics*, vol. 39, no. 1, pp. 645–664, 2022.

[3] W. Jin and S. Mou, "Distributed inverse optimal control," *Automatica*, vol. 129, p. 109658, 2021.