Inverse Reinforcement Learning for Dexterous Manipulation from Human Demonstration

Dexterous robotic hands try to reproduce the incredible capabilities and versatility of the human hand. However, due to their complexity, they are very difficult to control with traditional methods. Reinforcement Learning (RL) has shown great potential to solve multiple tasks in a data-driven way (e.g. solving a Rubik's cube [1]). A task is typically defined as a reward function and in RL, the agent learns to maximize this reward function. However, it can be difficult to define this reward function such that it encodes the correct task while still being easily optimizable. Existing work often utilizes extensive “reward shaping” to reach a satisfactory result but modern approaches try to circumvent this.

An alternative approach is Inverse Reinforcement Learning (IRL), which learns a reward function from expert demonstrations. The idea is that the expert optimizes a hidden reward function during the demonstrations. The goal is to find a reward function that maximizes the demonstrators actions. This learned reward function can be used with classical RL approaches to train a policy \( \pi(a|s) \).

There are multiple challenges and limitations of IRL that modern approaches try to address. Firstly, finding a cost function is an ill-defined problem. There are usually many reward functions that are maximized when executing the expert demonstrations. However, they often do not encode the intended task well. To arrive at a unique reward function, additional optimization goals can be added, e.g., to maximize entropy [2]. Another problem is how to deal with sub-optimal demonstrations and how to arrive at a policy which improves over the expert demonstrations. There is also recent work which specifically tackles this problem [3].

The goal of this project is to apply IRL to learn an in-hand manipulation task with the Shadow Robotic Hand from expert demonstrations. In a first step, different approaches in the literature should be investigated. The student should implement and compare multiple approaches with existing benchmark tasks in simulation\(^1\). The most suitable approach should be applied to the Shadow Robotic Hand environments.

**Tasks**

- Get familiar with the base concepts of RL and IRL. Investigate existing implementations of IRL algorithms.
- Implement and compare multiple IRL approaches for a simple Benchmark task.
- Become familiar with PyBullet and the teleoperation system for the Shadow Dexterous Hand, then create a new task in the simulator.
- Record demonstrations of the task using the teleoperation system.
- Apply IRL to learn an in-hand manipulation task from the demonstrations.

**Workload split**

- Research and theory: 30%
- Programming and implementation: 50%
- Writing: 20%

**Contact**

Matthias Hirschmanner, hirschmanner@acin.tuwien.ac.at

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\(^1\)https://gym.openai.com/envs/#classic_control
References

