SBP-Guided MPC to Overcome Local Minima in Trajectory Planning

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Motivation

- Trajectory planning is often a difficult task for high-dimensional systems, especially those with non-linear dynamics.
- Two common trajectory planning methods: Model Predictive Control (MPC) and Sampling-Based Planning (SBP).
- MPC: we use the iterative Linear Quadratic Gaussian (iLQG) algorithm
- SBP: we use Rapidly-exploring Random Trees (RRT) (Fig. 1)
- We hypothesize that the stochastic nature of RRT may help iLQG escape or avoid local minima.

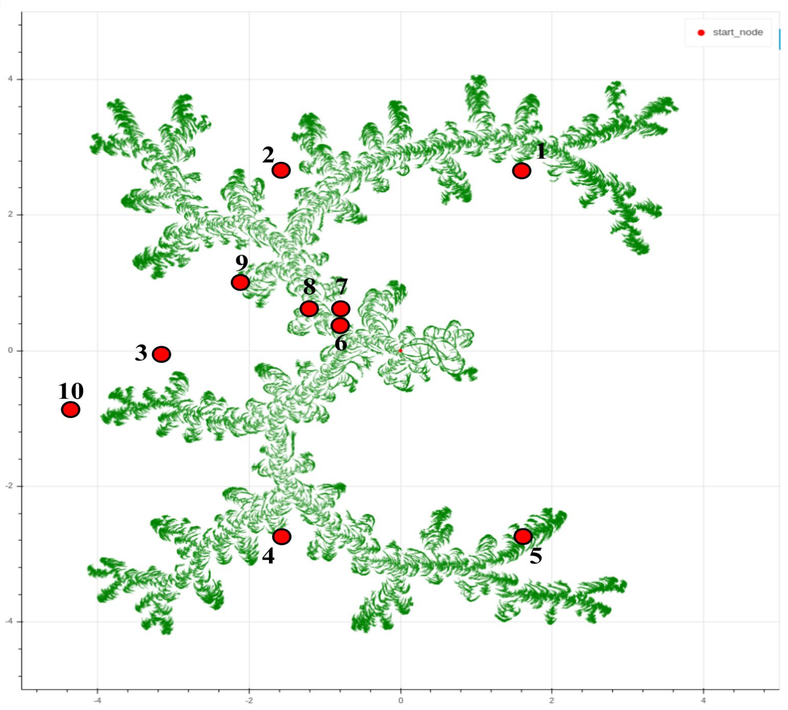


Figure 1: RRT tree of a 5-link snake with 310,000 nodes

Proposed Method: iLQG+RRT

Without tuning the cost function parameters individually for each goal, there is a subset of goal states for which iLQG either fails or takes a long time to reach. We suspect this is due to iLQG falling into local optima. To improve the performance of iLQG, we use trajectories generated by RRT in two different ways:

1. Create waypoint goals to split up computation for iLQG. (Fig. 2)
2. Use the action sequence of the RRT trajectory to provide a "warm start": an initial guess for iLQG to begin its optimization on. (Fig. 2)

With the iLQG+RRT method, we are able to quickly reach the subset of goals that iLQG alone either failed or took a long time to reach.

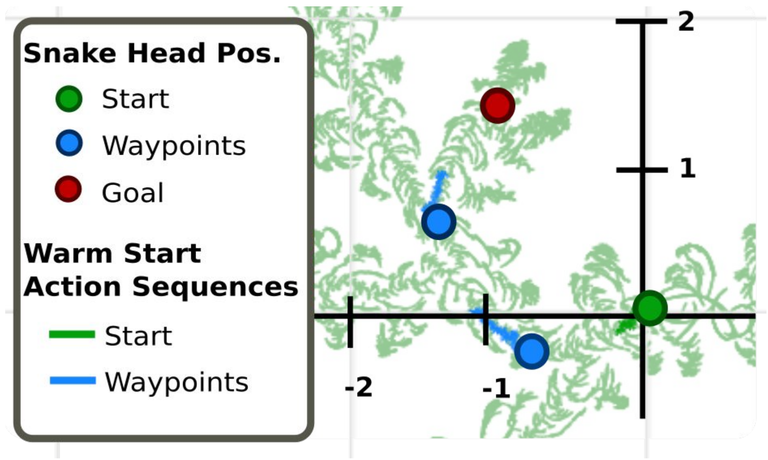


Figure 2: Waypoint goals and warm-start trajectories superimposed on the RRT tree from Fig. 1

Experiments

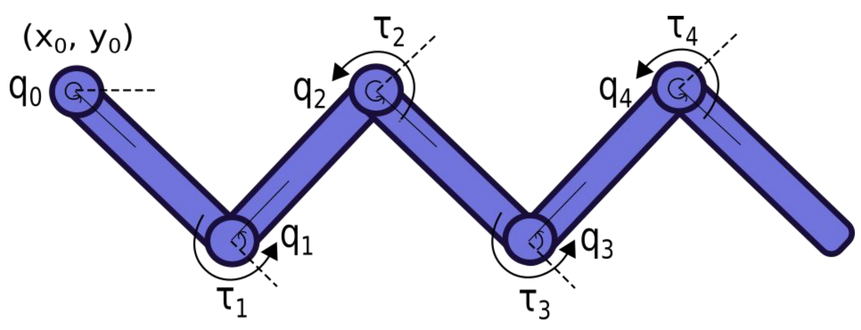
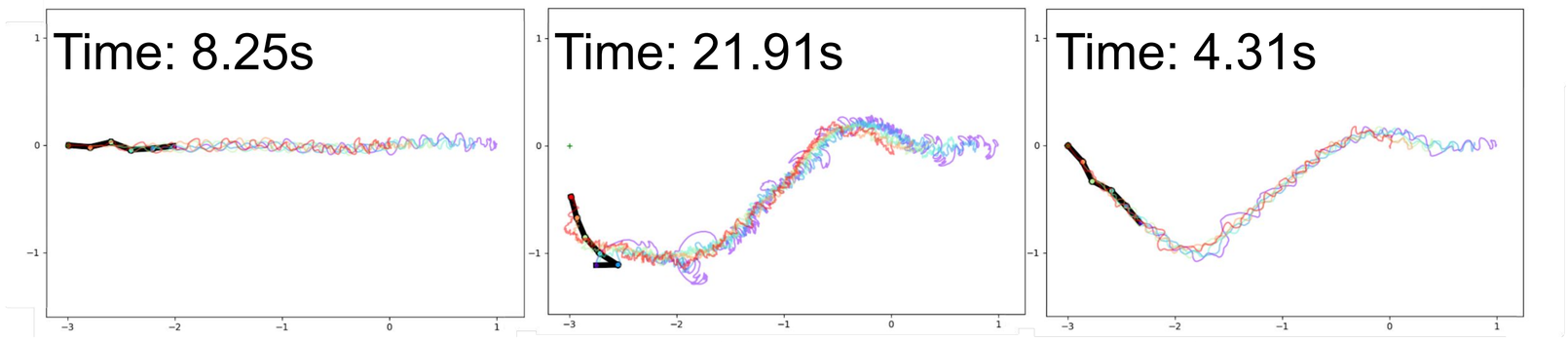


Figure 3: Five-Link 2D snake model



(a) iLQG (b) RRT (c) iLQG+RRT

Figure 4: Path of each joint as snake moves toward goal 3 from Fig. 1.

- We tested iLQG+RRT using a model of a five-link, 2D snake with anisotropic friction. (Fig. 3)
- For a subset of goals iLQG either fails (8, and 10) or is slow (3, 6, and 7) to reach the goal. In these cases, iLQG+RRT produces successful and fast trajectories to the goal. (Fig. 5)
- In goals where iLQG is successful (1, 2, 4, 5, and 9), iLQG+RRT and iLQG perform similarly. (Fig. 5)
- Fig. 4 shows an example of the improvement of iLQG+RRT.

Figure 5: Time for snake to reach goal. The goal number corresponds to the red points in Figure 1.

Recent Results

- If the cost function is not tuned for each individual goal, iLQG is also sensitive to the initial state configuration of the snake.
- We sampled 24 random initial states. For a goal of [-1, 0], iLQG failed in 4 out of 24 cases. (Fig. 6)
- We generated a RRT tree for each initial state. (Fig. 7)
- iLQG+RRT results in a good trajectory in each of these four cases.

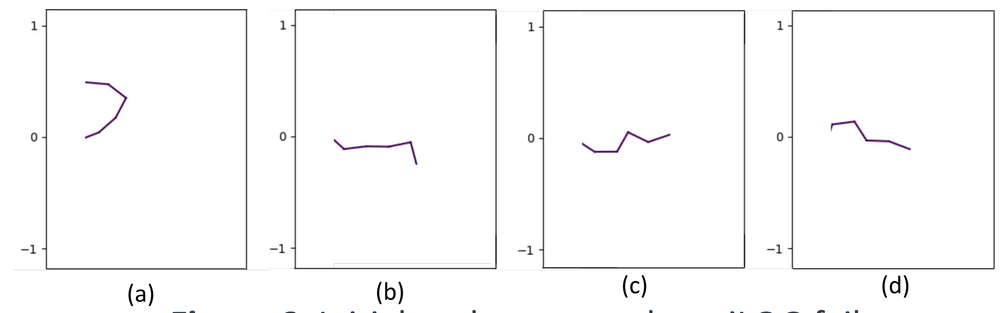


Figure 6: Initial snake states where iLQG fails

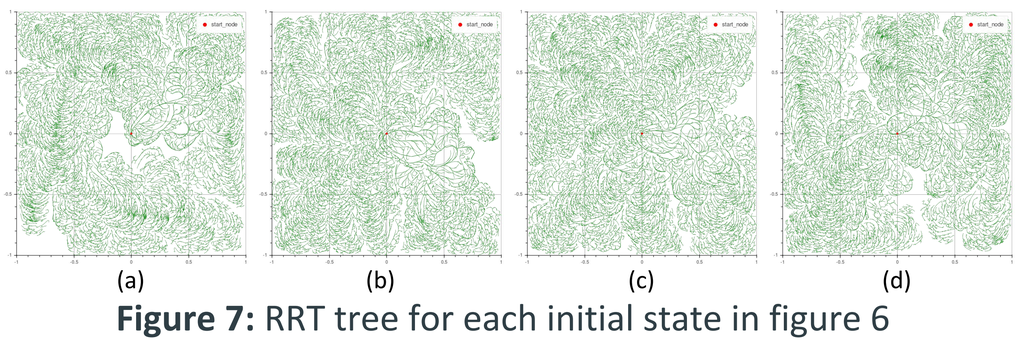
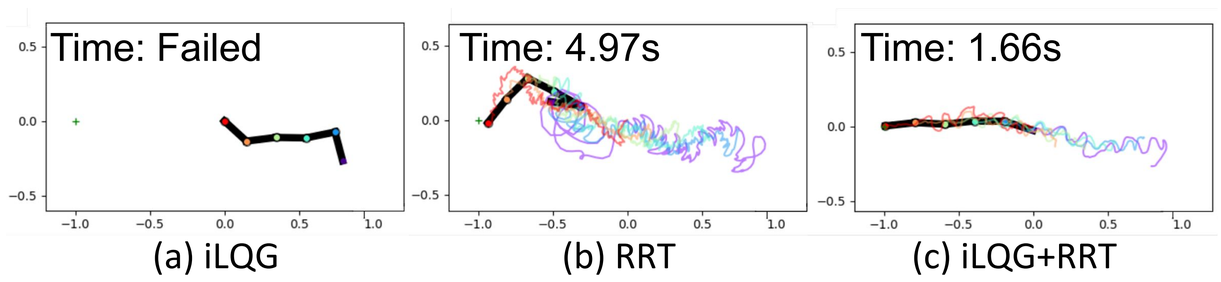


Figure 7: RRT tree for each initial state in figure 6



(a) iLQG (b) RRT (c) iLQG+RRT

Figure 8: Snake joint movement for Fig.6.b