RL-based Trajectory Generation for Collision-Free Fast Flight

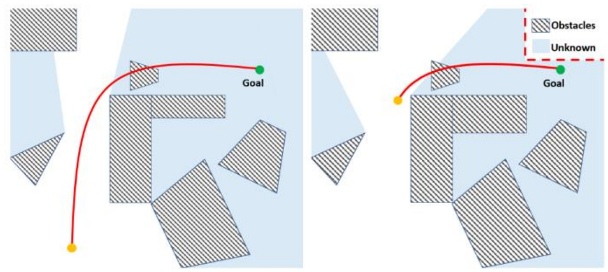

Figure 2: Generated trajectory in previously unseen region (shaded) leading to a collision. [4]

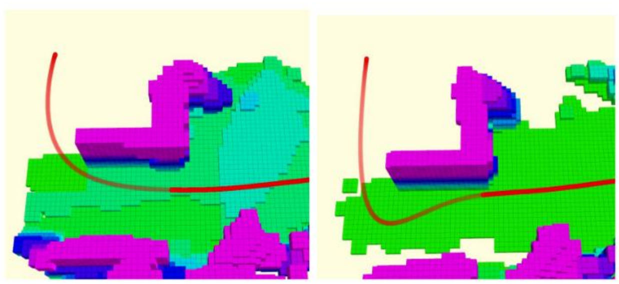

Figure 3: Examples of two trajectories that take the robot around the same region, with the second image allowing increased time to respond to previously unseen obstacles. [4]

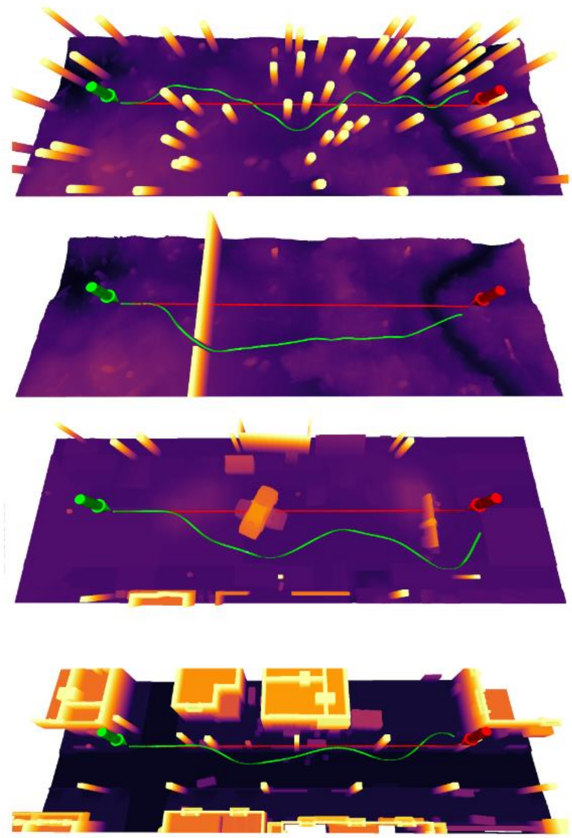

Figure 1: Examples of smooth trajectories for flight in different environments [2]

Abstract: Fast flight of an aerial robot in confined environments depends on several modules that sense, plan, map and control the robot independently. While this approach allows parallel development, they add a certain processing delay and take longer to complete, hindering fast flight. For collision avoidance, classical methods build a volumetric map that is prone to inconsistencies as the estimate of the robot's position drifts over time. A neural network can be used to directly take in a sequence of sensor measurements using a depth camera or a 3D lidar sensor, without using a map, to determine a set of parameters that are used to generate a smooth, collision-free trajectory for the robot. This process takes place iteratively, with the robot updating the trajectory at a given frequency, as it receives new sensor information. This thesis aims to design a neural network architecture and develop a method to train it to generate parameters for trajectories to reach a goal position in the environment. These trajectories must be smooth, collision-free and respect the dynamic constraints of the robot.

Tasks:

- Study:
  - papers related to classical motion planning and trajectory generation
  - Reinforcement learning methods (Q-learning, DDPG, TRPO, PPO)
- Understand and replicate various reinforcement learning algorithms
- Familiarize yourself with software tools and simulation environments
- Develop NN architecture and training pipeline for a simulated aerial robot
- Set up a simulation pipeline using the available tools for generating trajectories in free space.
- Train the neural network to generate trajectories iteratively as the simulated robot follows them
- Evaluate trained network using simulation and real experiments

Literature (indicative):

[1] Nguyen, Huan, et al. "Motion Primitives-based Navigation Planning using Deep Collision Prediction." arXiv preprint arXiv:2201.03254 (2022). [https://arxiv.org/abs/2201.03254]

[2] Loquercio, Antonio, et al. "Learning high-speed flight in the wild." Science Robotics 6.59 (2021). [https://arxiv.org/abs/2110.05113]

[3] A. Loquercio, A. I. Maqueda, C. R. del-Blanco and D. Scaramuzza, "DroNet: Learning to Fly by Driving," in IEEE Robotics and Automation Letters 2018. [https://ieeexplore.ieee.org/document/8264734]

[4] Zhou, Boyu, et al. "Raptor: Robust and perception-aware trajectory replanning for quadrotor fast flight." IEEE Transactions on Robotics 37.6 (2021): 1992-2009. [https://arxiv.org/abs/2007.03465]

[5] D. Mellinger and V. Kumar, "Minimum snap trajectory generation and control for quadrotors," 2011 IEEE International Conference on Robotics and Automation, 2011. [https://ieeexplore.ieee.org/document/5980409]

[6] Liu, Sikang, et al. "Search-based motion planning for aggressive flight in se (3)." IEEE Robotics and Automation Letters 3.3 (2018): 2439-2446. [https://arxiv.org/abs/1710.02748]

Relevant Funded Project:

- **Title**: RESNAV: Resilient Assured Learning-based Autonomous Navigation
- **Funding Agency**: US Air Force Office of Scientific Research

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