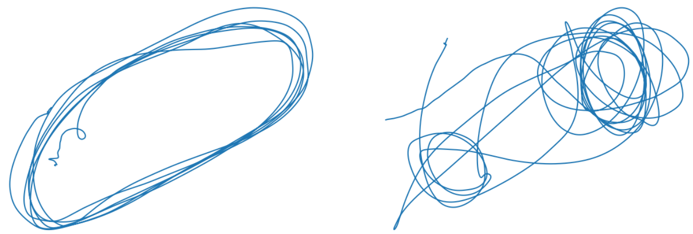

Figure 1: Example flight trajectories from the UZH FPV Dataset [1]

GAN Enabled Drone Trajectory Prediction

Stanford CS236G Final Project

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Code available at https://github.com/aksbaih/drone-trajectory.

Dataset.

I'm using the UZH FPV Dataset [1] for this project. The authors of this dataset wanted to challenge the state of the art state estimation models in UAV racing by introducing highspeed manuevers in real-world environments. This task aims to approximate the trajectory and momentum of the drone based on minimal sensory input (in this case, the grayscale view through a camera attached to the drone). The dataset consists of frames taken at 50Hz tied to a ground truth representing the momentum around each of the 6 degrees of freedom the drone has in 16 flights lasting around 100 seconds each.

I'm reusing the dataset for a different task here: I'm interested in predicting the immediate trajectory of a drone based on its location history as observed from a third-party. This trajectory info is embedded in the ground truth of the original dataset. Therefore, I use the dataset toolbox and my own code in the linked repo to generate the xyz location of the drone at each frame of a constant FPS and store it locally as a txt file for each flight. Since I'm going to be using transformers, I reduce the FPS to 8 instead of 50 to span larger trajectory in less memory but this is subject to change based on later experiments. This totals 11486 frames. Figure 1 shows example trajectories.

Since the number of flights is not very big and each flight has a different pattern of trajectories, I reused the method of [2] where the validation set is sampled as random windows of the training set when constructing the dataloader. I'm using 64 frames from each flight for validation, making around 9% (1k frames) of all frames, but this could increase if needed. For the testing set, I left aside two flights that were considered "medium" according to [1] consisting of 1.9k frames, or 17% of the original count. This leaves 74% (8.6k frames) for training.

References

[1] Jeffrey Delmerico, Titus Cieslewski, Henri Rebecq, Matthias Faessler, and Davide Scaramuzza. Are we ready for autonomous drone racing? the UZH-FPV drone racing dataset. In *IEEE Int. Conf. Robot. Autom. (ICRA)*, 2019.

[2] Francesco Giuliari, Irtiza Hasan, Marco Cristani, and Fabio Galasso. Transformer networks for trajectory forecasting, 2020.