

FUEL Learning Poster

Tags: Motion Planning, Flying Robots

(Reference: Zhou, Boyu, et al. "Fuel: Fast uav exploration using incremental frontier structure and hierarchical planning." IEEE Robotics and Automation Letters 6.2 (2021): 779-786.)

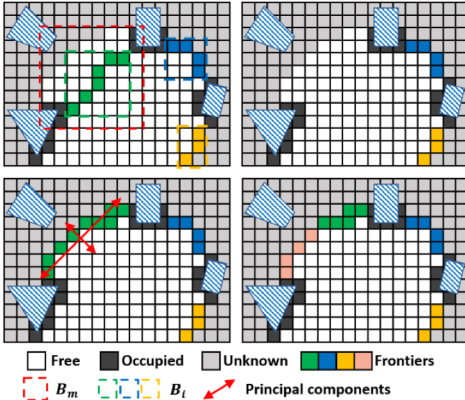
Problems

1. Greedy exploration leads to local optimality, and most methods are conservative. → Solved by hierarchical planning.
2. Low-speed exploration, disallows fully exploit dynamic capability to fulfill the mission. → Solve
3. Due to high computational overhead, quadrotor can not respond quickly and frequently to environmental changes. → Solve

Eliminate unaffected clusters in a fast way, significantly reduce number of expensive precise checks.

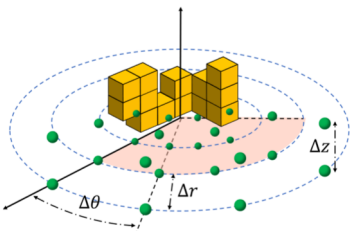
A. Remove outdated frontier clusters:

- a. Record the AABB B_m of the updated region, select clusters whose AABBs (B_i) intersect with B_m .
- b. Precise check on selected clusters, remove clusters containing cells that are no longer frontier.



B. Frontier Detection: Search and cluster new frontier clusters by region growing algorithm, ignore small ones (typically from noise).

C. Clustering: Recursively conduct PCA until all large clusters are divided into small ones.



- A. Uniformly sampled viewpoints set $VP_i = \{x_{i,1}, x_{i,2}, \dots, x_{i,n_i}\}$, $x_{i,j} = (p_{i,j}, \xi_{i,j})$
- B. Filter (at most reserve N_{view} viewpoints) and sort VP_i in descending order by coverage.

Updating when new frontiers are detected, leads to more frequent and faster speed exploration.

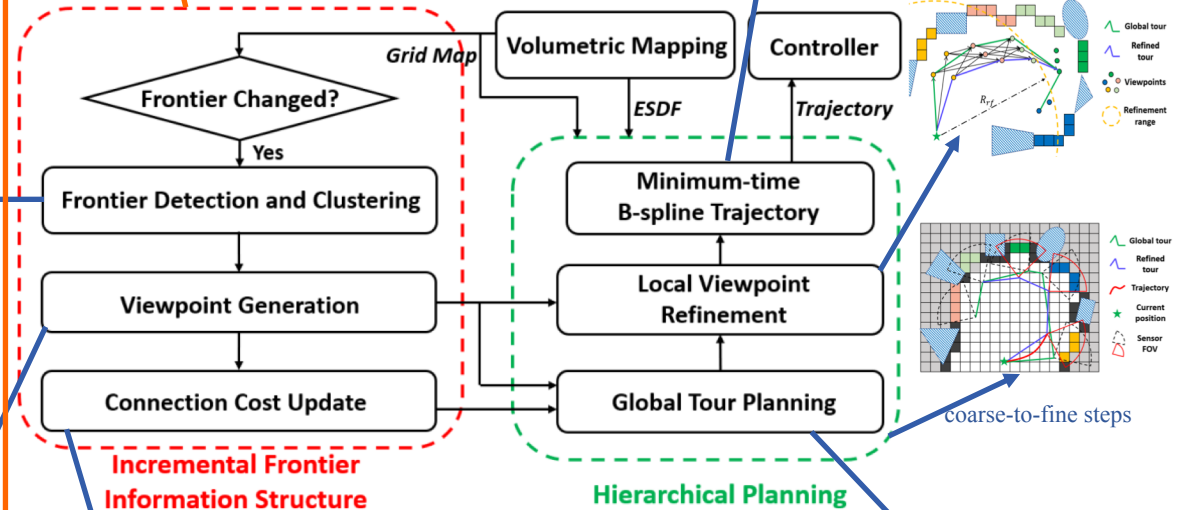
Minimum-time B-Spline Trajectory: Generate smooth, safe and dynamically feasible B-spline trajectories

$$\arg \min_{\mathbf{X}_{c,b}, \Delta t_b} f_s + w_t T + \lambda_c f_c + \lambda_d (f_v + f_a) + \lambda_{bs} f_{bs}$$

Local Viewpoint Refinement: Only a single viewpoint of each cluster \rightarrow a richer set of viewpoints on a truncated segment of the global tour.

Use Dijkstra to find optimal local tour $\Xi = \{x_{1,j_1}, x_{2,j_2}, \dots, x_{N_{tr},j_{N_{tr}}}\}$ by min:

$$c_{tr}(\Xi) = t_b(x_0, x_{1,j_1}) + w_c \cdot c_c(x_{1,j_1}) + t_b(x_{N_{tr},j_{N_{tr}}}, x_{N_{tr}+1,1}) + \sum_{k=1}^{N_{tr}-1} t_b(x_{k,j_k}, x_{k+1,j_{k+1}})$$



Select viewpoints with highest coverage to estimate connection cost as:

$$t_{lb}(x_{k_1,1}, x_{k_2,1}) = \max \left\{ \frac{\text{len}(P(p_{k_1,1}, p_{k_2,1}))}{v_{max}}, \frac{\min(|\xi_{k_1,1} - \xi_{k_2,1}|, 2\pi - |\xi_{k_1,1} - \xi_{k_2,1}|)}{\xi_{max}} \right\}$$

$P(p_{k_1,1}, p_{k_2,1})$ is searched using A*.

- a. Above update scheme takes $O(k_{new} \cdot N_{cls})$ time.
- b. k_{new} can be regarded as a constant factor, resulting in a linear time update.

Global Exploration Tour Planning: Compute an open-loop tour starting from current and passing all clusters by ATSP.

For cost matrix M_{fcn} :

$$M_{isp}(k_1, k_2) = M_{isp}(k_2, k_1) = t_{lb}(x_{k_1,1}, x_{k_2,1}), \quad k_1, k_2 \in \{1, 2, \dots, N_{cls}\}$$

$$M_{isp}(0, k) = t_{lb}(x_0, x_{k,1}) + w_c \cdot c_c(x_{k,1}), \quad k \in \{1, 2, \dots, N_{cls}\}$$

$$c_c(x_{k,j}) = \cos^{-1} \frac{(\mathbf{p}_{k,j} - \mathbf{p}_0) \cdot \mathbf{v}_0}{\|\mathbf{p}_{k,j} - \mathbf{p}_0\| \cdot \|\mathbf{v}_0\|}$$

$$M_{isp}(k, 0) = 0, \quad k \in \{0, 1, 2, \dots, N_{cls}\}$$

Summarization and Personal Thinking

Summarization:

1. Innovation:

- a. Maintained FIS (Frontier Incremental Structure) for hierarchical planning:

Due to this incremental updated structure, quadrotor makes decisions at high frequency to respond quickly to environmental changes.

- b. Coarse-to-fine hierarchical planner for global coverage and reducing conservation:

- b.1 For global optimality, it firstly finds efficient global tours (coarse).

- b.2 Then selecting a local set of optimal viewpoints for refinement.

- b.3 Minimum-time B-spline local trajectories are generated at last to guarantee safety and dynamical feasibility.

2. Limitation:

Error in state estimation should not be ignored.

Future Work and Personal thinking:

- 1. Consider state estimation uncertainty, and evaluate under pose drifts (mentioned in paper).
- 2. Consider about methods which model planner as learned dynamics (using reinforcement learning or neural-network with mathematical constraints), FUEL can be combined with these “learning” related methods.
- 3. Expert demonstration learning and intervention learning could be applied in this scenario, and “trial and error” methods are also suitable in fast UAV motion planning.