Autonomous Exploration

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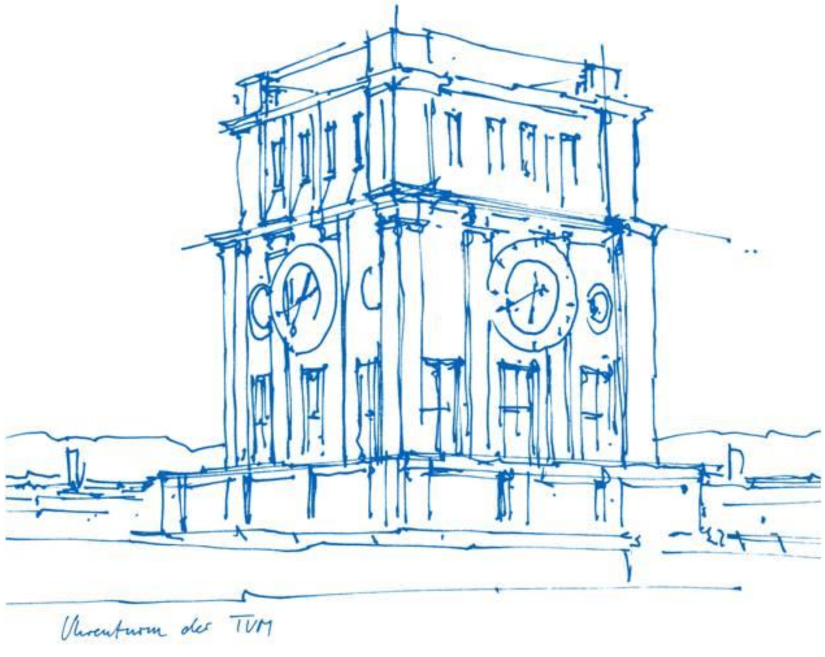

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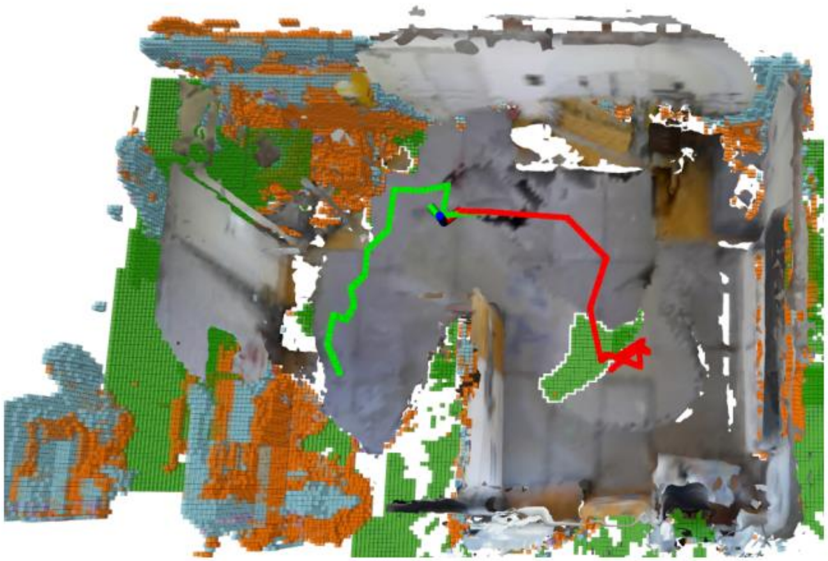
Motivation



Source: [1]

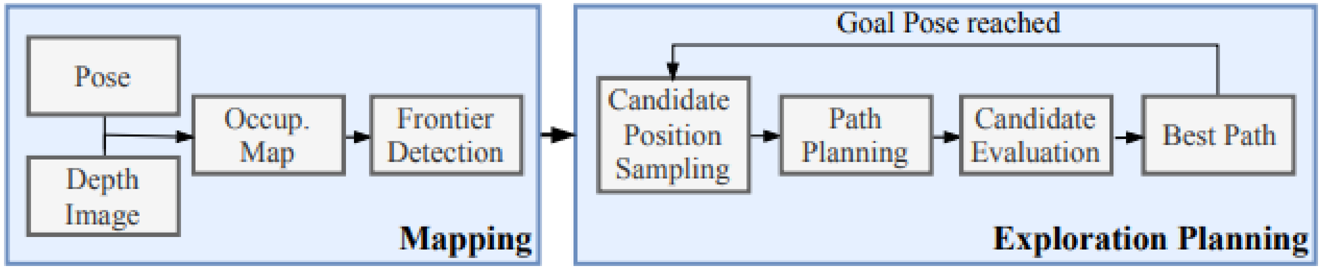
Autonomous Exploration

How to **map** an **unknown volume** ***V*** in a **safe** and **efficient** manner?

$$P_0^*, \ldots, P_{N_P}^* = \underset{P_0, \ldots, P_{N_P}}{\arg\max}\ O(M_{N_P})$$

Next Best View (NBV) Problem

What is the **best next pose to gain information** about the **volume** from the **sensor**?



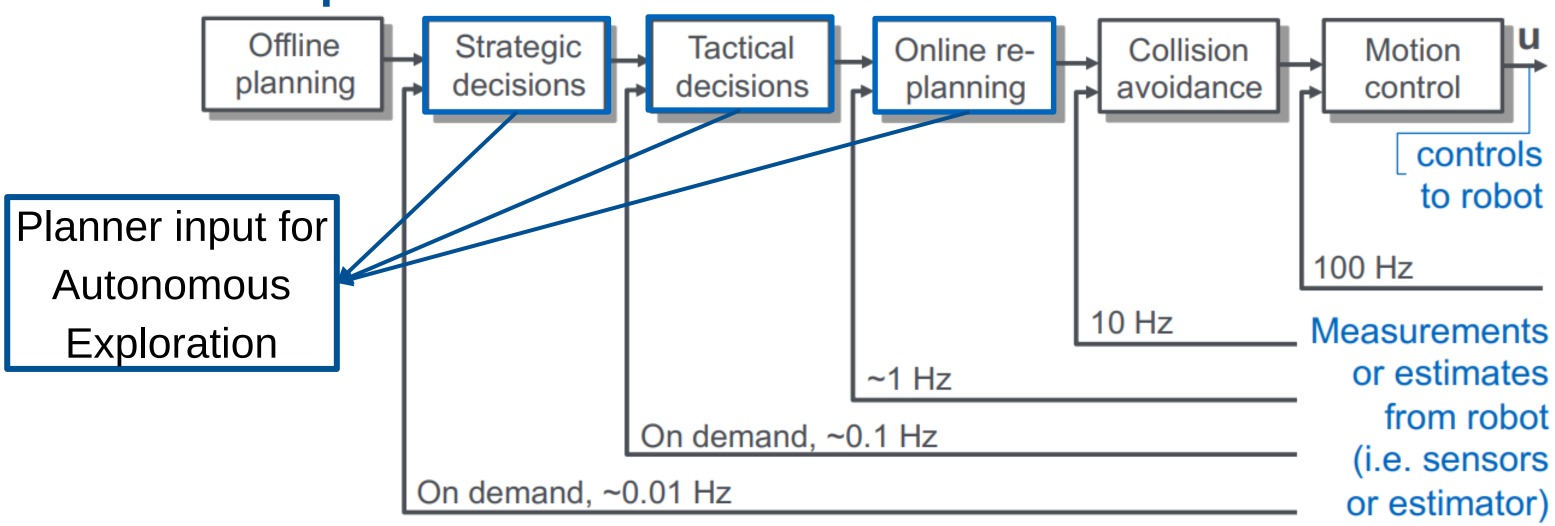
Source: [2]

Terminology

Definitions

- **Free volume**: V_{free} with some probability $1 - P_v(o)$
- **Occupied volume**: V_{occ} with some probability $P_v(o)$
- **Observed volume**: $V_{obs} = V_{free} \cup V_{occ}$
- **Residual volume**: $V_{res} = V \setminus V_{obs}$
- **Frontier**: observed map volume next to unobserved map volume

Control Loop



Source: [3]

Related Work

Sampling Based Explorer
- Bircher et al [4]
- 2016
- Volumetric and surface exploration
- Arbitrary depth sensor

Frontier Based Explorer
- Dai et al [2]
- 2020
- Volumetric exploration
- Arbitrary depth sensor

Scene Completion Explorer
- Schmid et al [1]
- 2022
- Volumetric exploration
- RGBD image

Other Types
- Optimization based
- Physics inspired

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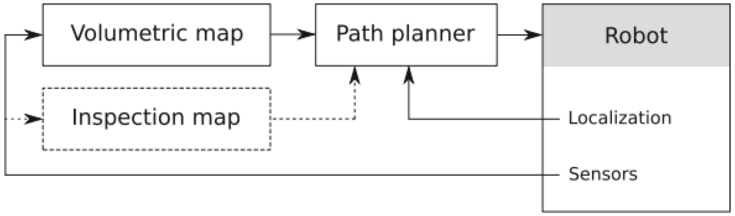
Methods I: Sampling Based Explorer [4]

Idea

Grow **a geometric tree** in **free space**, extract the branch with the **highest gain** and execute the **first segment** of that branch. **Iteratively** repeat this per timestep, i.e., **receding horizon path planning**.



Implementation Details

- Drone state: $\xi = (x, y, z, \psi)^T$
- Gain of node n_k:

$$\mathbf{Gain}(n_k) = \mathbf{Gain}(n_{k-1}) + \mu(\mathbf{Visible_V}(\mathcal{M}, \xi_k))e^{-\lambda c(\sigma_{k-1}^k)}$$

- Geometric tree building: RRT
  - Reinitialize with remainder of best branch
  - Maximum depth N_{max} and N_{Tol}
- Map M: octree representation
- Initialization procedure

Algorithm 1 Exploration Planner—Iterative Step

```
ξ_0 ← current vehicle configuration
Initialize 𝕋 with ξ_0 and, unless first planner call, also with previous
best branch
g_best ← 0                                        ▷ Set best gain to zero
n_best ← n_0(ξ_0)                                 ▷ Set best node to root
N_𝕋 ← Number of initial nodes in 𝕋
while N_𝕋 < N_max or g_best = 0 do
    Incrementally build 𝕋 by adding n_new(ξ_new)
    N_𝕋 ← N_𝕋 + 1
    if Gain(n_new) > g_best then
        n_best ← n_new
        g_best ← Gain(n_new)
    if N_𝕋 = N_TOL then
        Terminate exploration
σ ← ExtractBestPathSegment(n_best)
Delete 𝕋
return σ
```

Methods II: Frontier Based Explorer [2]

Idea

Sample **candidates** for the **NBV** from **frontiers**. A **specific octree map representation** allows for **fast clustering** of the **frontier**. **Sparse raycasting** and **Shannon entropy** is utilized to calculate the **information gain** of a candidate pose.

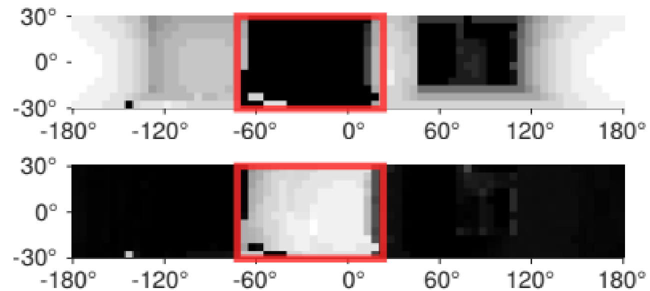
Implementation Details

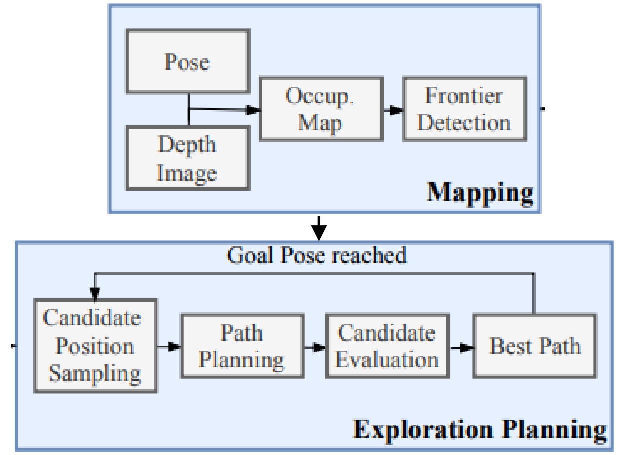
- Drone state: $\mathbf{x} = (x, y, z, \psi)^T$
- Map M: octree representation using *supereight* [8] and Morton codes for spatial indexing
- Two step sampling process for candidate poses $\mathbf{x}_i$
- Shannon's entropy and utility of a candidate pose:

$$\mathbb{H}(\mathbf{v}) = -P_o(\mathbf{v}) \ln P_o(\mathbf{v}) - (1 - P_o(\mathbf{v})) \ln (1 - P_o(\mathbf{v}))$$

$$u(\mathbf{x}_i, \hat{W}_i) = \frac{\mathbb{H}(\mathbf{x}_i)}{T(\hat{W}_i)}$$

- Path planner to selected NBV: informed RRT*
- Optimize yaw for best path nodes from RRT*

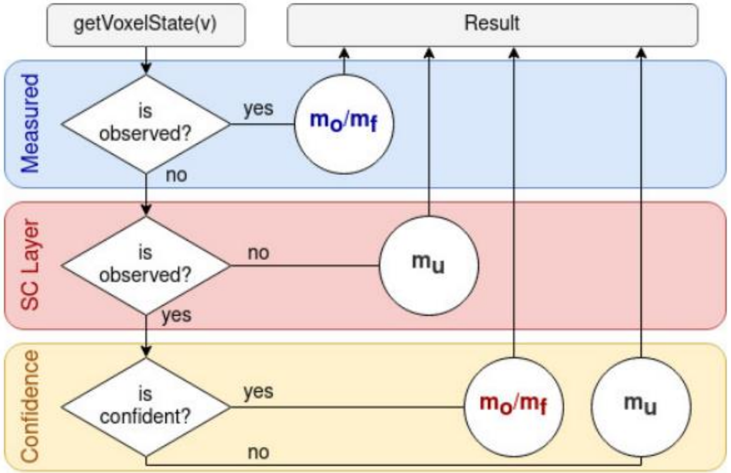




Methods III: Scene Completion Explorer [1]

Idea

Deploy a **neural network** for incremental **Scene Completion (SC)**. Utilize the SC in a **hierarchical map** to **improve** the **mapping** and the **planning** of the SC Explorer and therefore the exploration itself.



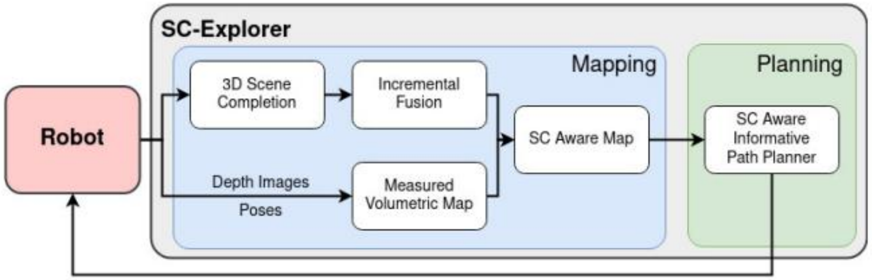
Implementation Details

- Drone state: $\mathbf{x} = (x, y, z, \psi)^T$
- Sampling based approach for NBV [9]
- Map M: TSDF Map
- Path planning with and without SC layer
- Utilization of SC estimates for ray casting
- Information gains based on measurements, SC layer or both, e.g.,

$$I_{sc}(v) = \begin{cases} 1, & \text{if } v \in \mathbb{P} \\ 0, & \text{otherwise} \end{cases}$$

Volume predicted by SC

- Utility of nodes based on information gain and traversal time of path segments



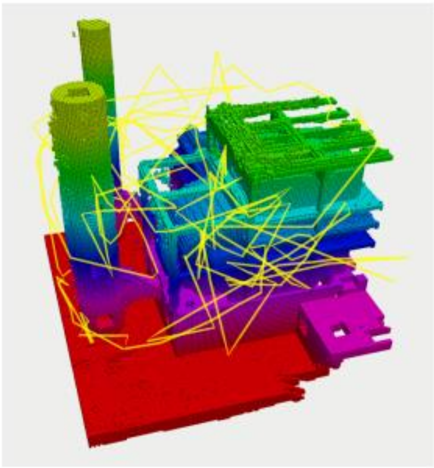
Results I

Task:

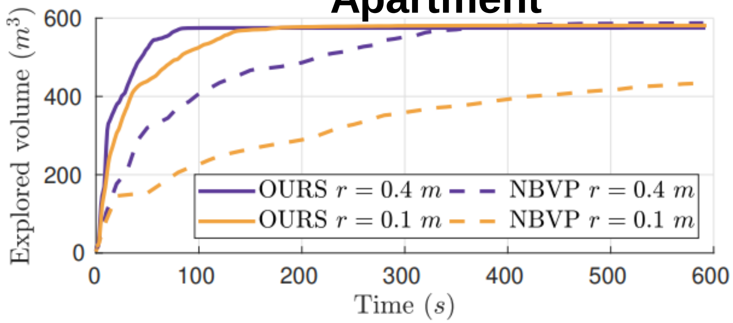
Explore a volume of $10\ x\ 20\ x\ 3\ m^3$, $20\ x\ 20\ x\ 2.5\ m^3$, and $33\ x\ 31\ x\ 26\ m^3$

Planner

Sampling based planner vs frontier based planner

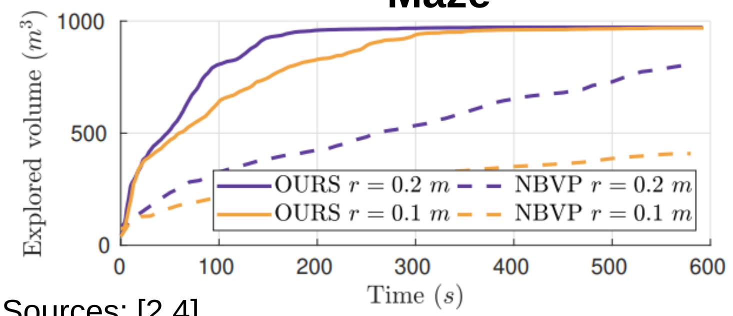


Apartment



	r (m)	Apartment (ms)	Maze (ms)	Powerplant (ms)
	0.4	122 ± 36	–	–
Ours	0.2	156 ± 109	155 ± 71	152 ± 20
	0.1	68 ± 27	238 ± 80	–
	0.4	73 ± 8	–	–
NBVP	0.2	707 ± 44	775 ± 50	–
	0.1	7940 ± 410	8540 ± 425	–

Maze



Takeaways

- Better scaling with higher map resolution
- Better global performance
- Anomaly in computation time for apartment and $r\ =\ 0.1\ m$ for frontier based planner

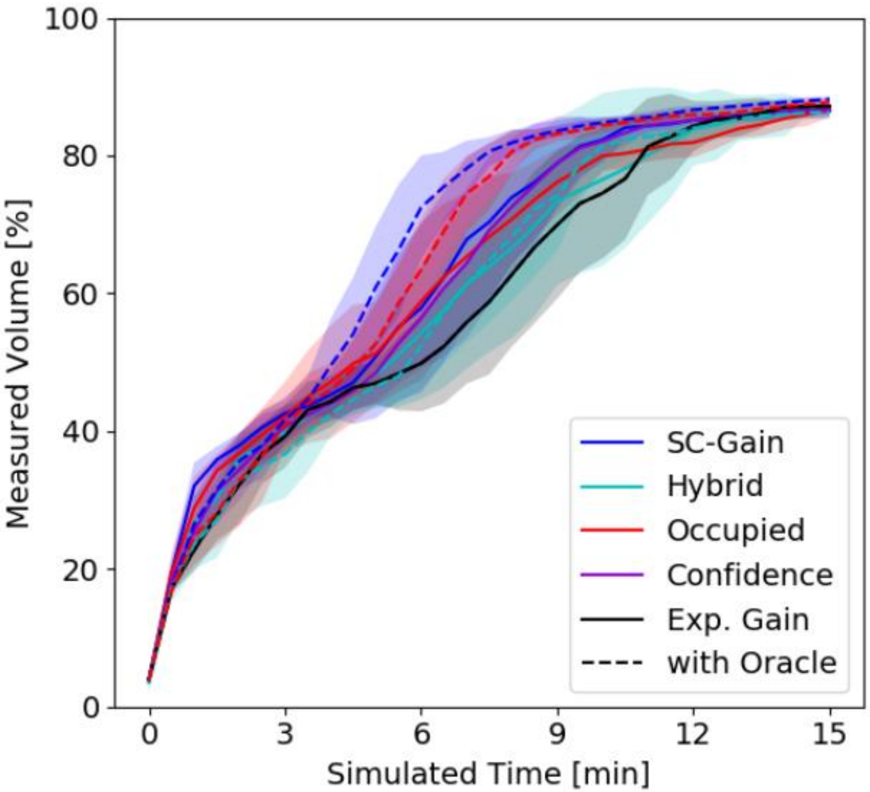
Sources: [2,4]

Results II

Performance gains using SC Explorer

- Mapping time improved with some decline of the mapping accuracy
- Using SC in planning speeds up performance but safety is not guaranteed
- Using SC for raycasting decreases performance of SC Explorer compared to oracle

> ➡ Performance of SC Explorer depends on quality of prediction of the SC



Source: [1]

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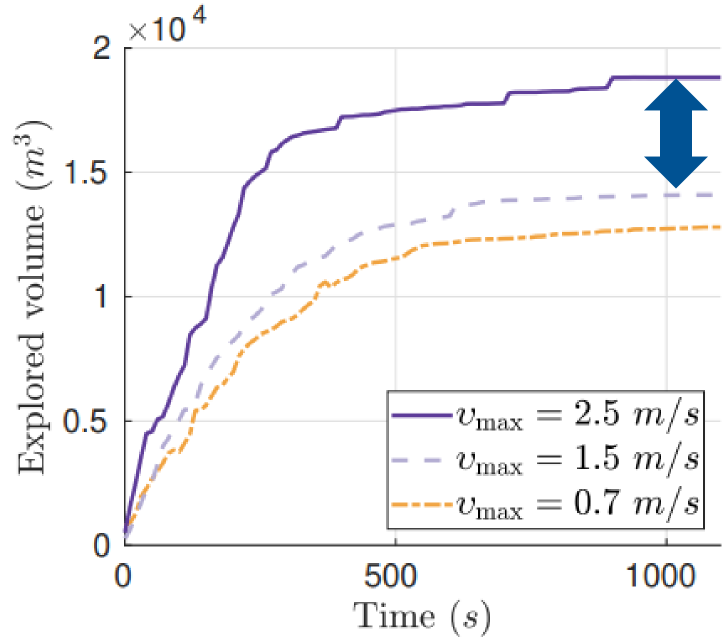
Comments I

Influence of Path Cost in Utility and on Final Performance

- Utility of Frontier based explorer with estimated completion time of path $T(\widehat{W}_i)$ assuming maximum linear speed

$$u(\mathbf{x}_i, \hat{W}_i) = \frac{\mathbb{H}(\mathbf{x}_i)}{T(\hat{W}_i)}$$

- Different performance for different v_{max} due to influence of v_{max} on utility of candidate poses



Source: [2]

Curse of Dimensionality

- Frontier based: RRT* in 3 DoF
- Sampling based planner extension [5]

Comments II: Comparison of Methods

Metric / Characteristic	Sampling Based Explorer	Frontier Based Explorer	Scene Completion Explorer
Computational Complexity / Execution Times	**o** Worse performance with decreasing map resolution	**+** Better performance then sampling based	**-** SC computational expensive ~ 1Hz
Hyperparameters	• Weighting of path cost • Horizon	• Weighting of path cost • Sparse raycasting	• Probabilities for logs-odd updates • Confidence cut-off • (SC neural network)
Information Gain	Only volume of unmapped visible voxels	Mapped voxels with high uncertainty are also considered in entropy	SC as heuristic / prior for exploration
Exploration Speed	**o**	**+**	**+**
Safety	No collisions reported	No collisions reported	Optimistic planner/ naive TSDF not guaranteed safe

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Dynamic Flight
- 6 DoF Drone Model
- Optimization based path planning
- Potential increase in performance since travel cost is more accurately estimated

Uncertainty aware SC
- Occupation probabilities and confidence cut-off hand tuned for SC
- Uncertainty aware SC for better performance including blocking raycasting

Safety / Reliability
- Classical TSDF map not safe due to artifacts / optimistic planning based on SC
- Multiple sensors / multi-resolution mapping pipeline
- Safety Layer / Reactive Avoidance [6]

Dynamic Environments
- All approaches presented today assume static environments
- First Step: Object Centric Exploration [7]

Sources

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[4] A. Bircher, M. Kamel, K. Alexis, H. Oleynikova, and R. Siegwart, “Receding horizon path planning for 3D exploration and surface inspection,” *Auton. Robots*, vol. 42, no. 2, pp. 291–306, Feb. 2018, doi: 10.1007/s10514-016-9610-0.

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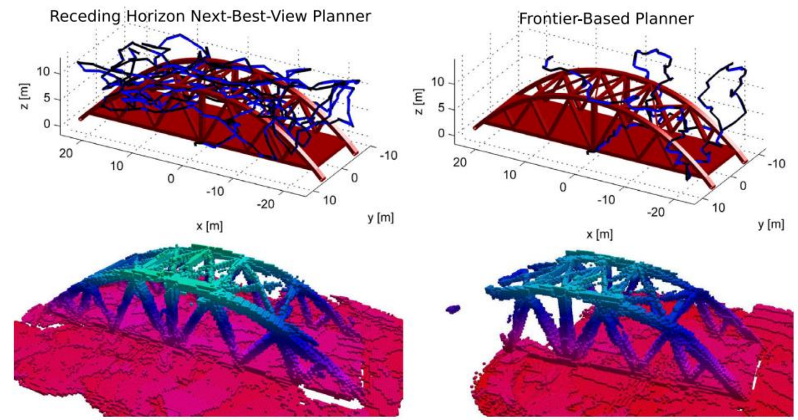
[8] E. Vespa, N. Nikolov, M. Grimm, L. Nardi, P. H. J. Kelly, and S. Leutenegger, “Efficient octree-based volumetric SLAM supporting signed-distance and occupancy mapping,” IEEE Robotics and Automation Letters, vol. 3, no. 2, pp. 1144–1151, Apr. 2018.

[9] L. Schmid, M. Pantic, R. Khanna, L. Ott, R. Siegwart, and J. Nieto, “An efficient sampling-based method for online informative path planning in unknown environments,” IEEE Robotics and Automation Letters, vol. 5, no. 2, pp. 1500–1507, April 2020

Additional Slides: Results [4]



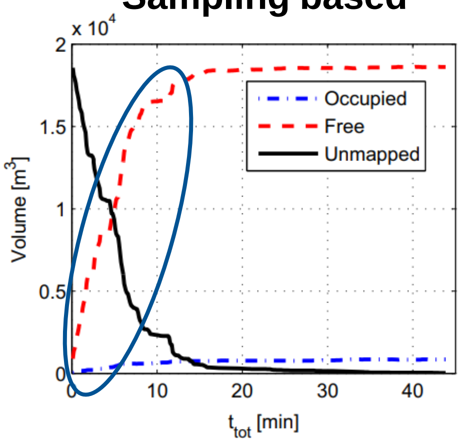
Task:

Explore a volume of $50\ x\ 26\ x\ 14\ m^3$

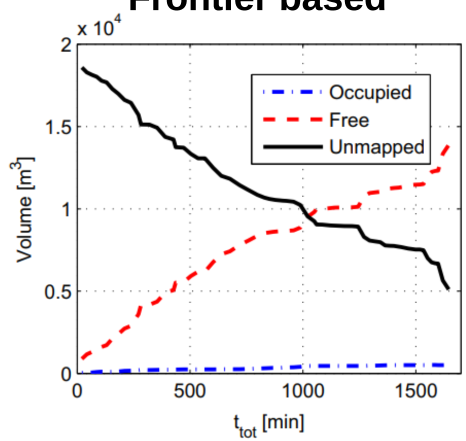
Planner

Sampling based planner vs Frontier based planner from 2002

Sampling based



Frontier based



Metric	Sampling based	Frontier based
t_{tot}	$\mathbf{43.8\ min}$	$1670.1\ min$
$t_{comp,tot}$	$\mathbf{9.4\ min}$	$1660.4\ min$
$\bar{t}_{comp}$	$\mathbf{1.6\ s^*}$	$25.9\ min$

* With a maximum of replanning time of $23\ s$ and map resolution of $\mathrm{r} = 0.25\ \mathrm{m}$

→ **Greedy, local planner**

Additional Slides: Comments

Locality of sampling based approaches

- SC Explorer utilizes a sampling based planner
- Greedy and local planner
- Good initial performance, then local minimum (★) until new large area of unmapped space is found