Sensing Ability Based Exploration

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0. Background

Representing Space

As for most sensors the perception stops at surfaces, hollow spaces or narrow pockets can sometimes not be explored with a given setup. This residual space denoted by V_{res}

3D space $V \subset \mathbb{R}^3$ initially unmapped space $V_{unm} \overset{init.}{=} V$

free $V_{free} \subset V$ or occupied $V_{occ} \subset V$

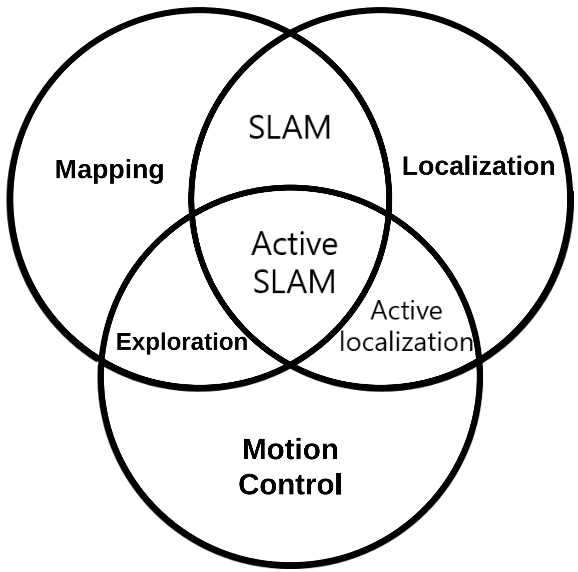
Purpose of Exploration

$\boxed{\text{unmapped exploration area } V_{unm}}$

$$\boxed{V_{free} \cup V_{occ} = V \setminus V_{res}}$$

0. Background

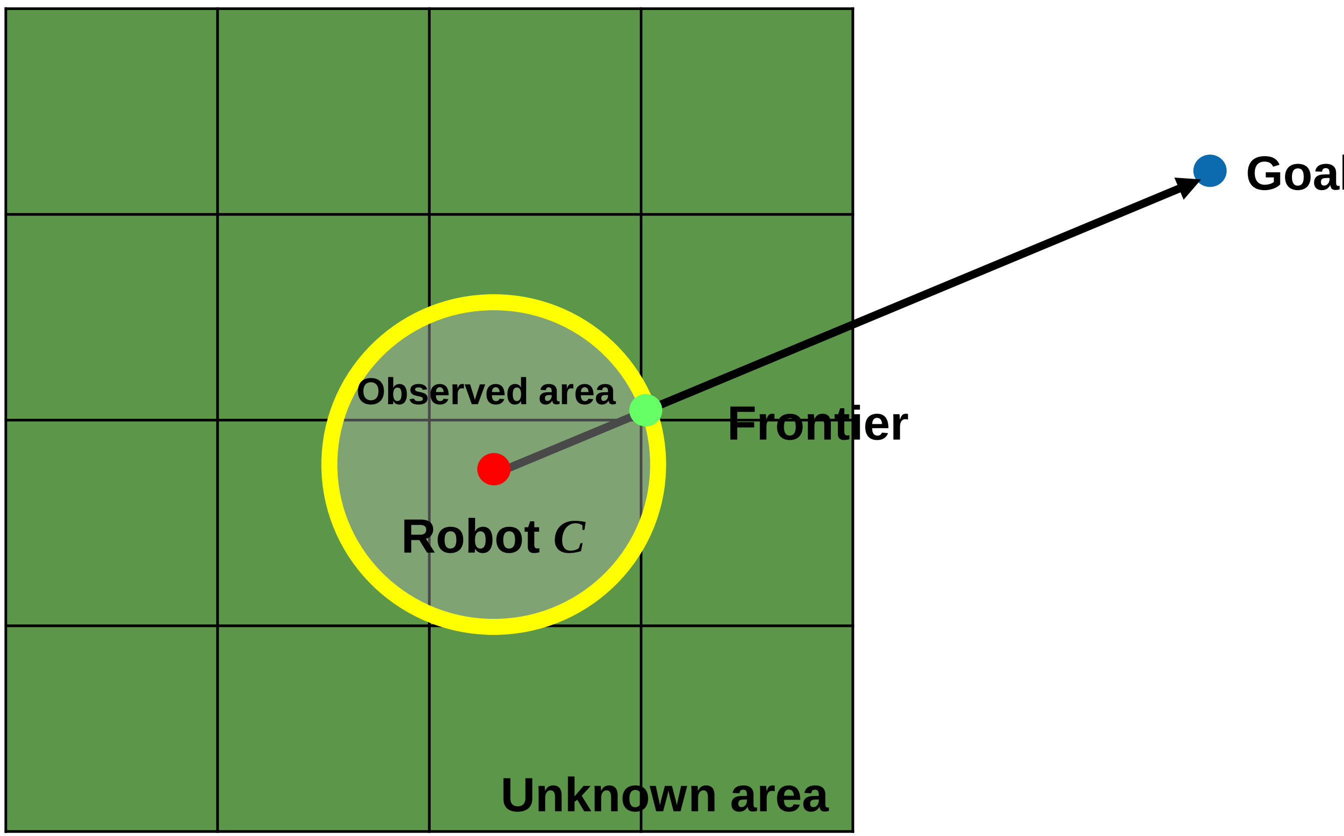
- Exploration
  - Map is used for both, collision free navigation and determination of the exploration progress



0. Background

Previous Exploration Method

- Frontier Based Exploration is one of them
- To gain the most new information about the world, move to the boundary between known space and unknown space



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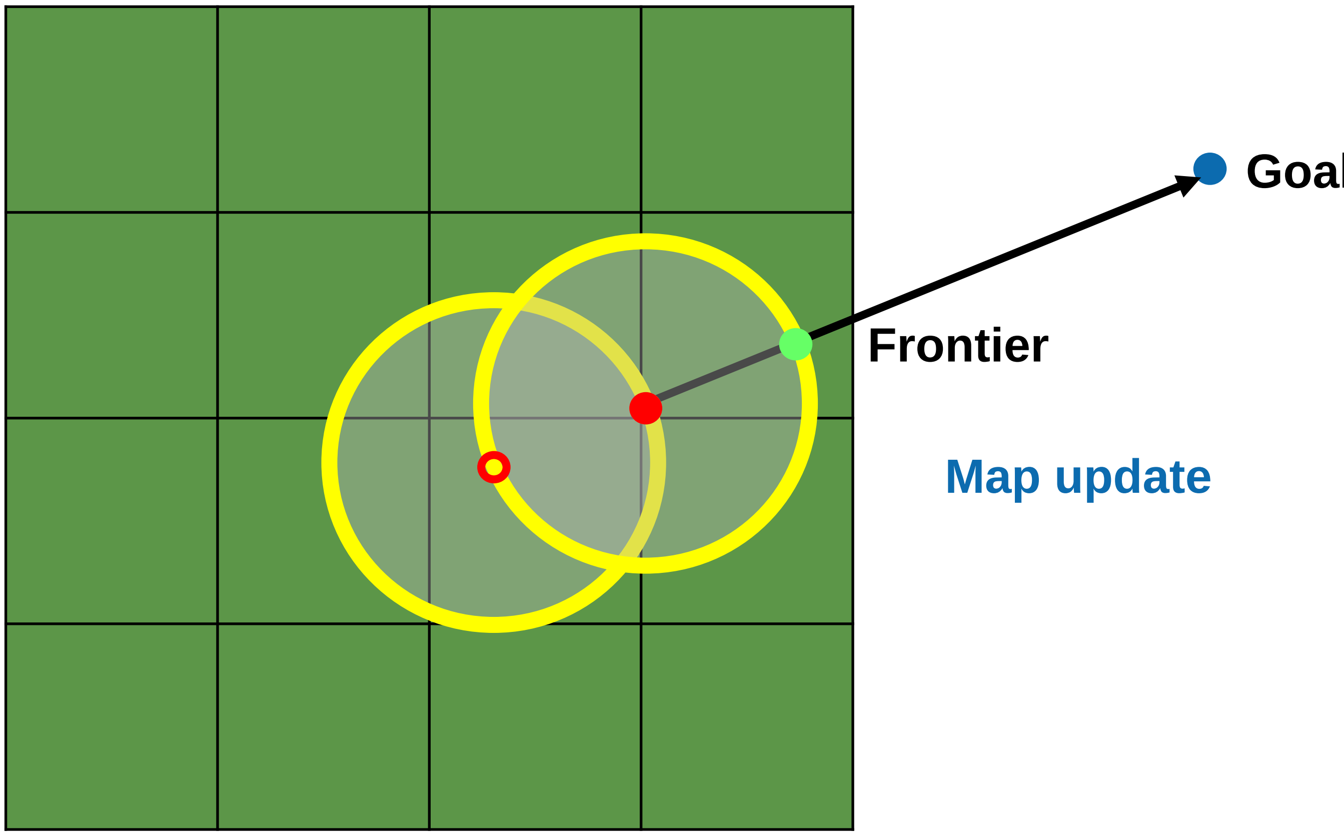


0. Background

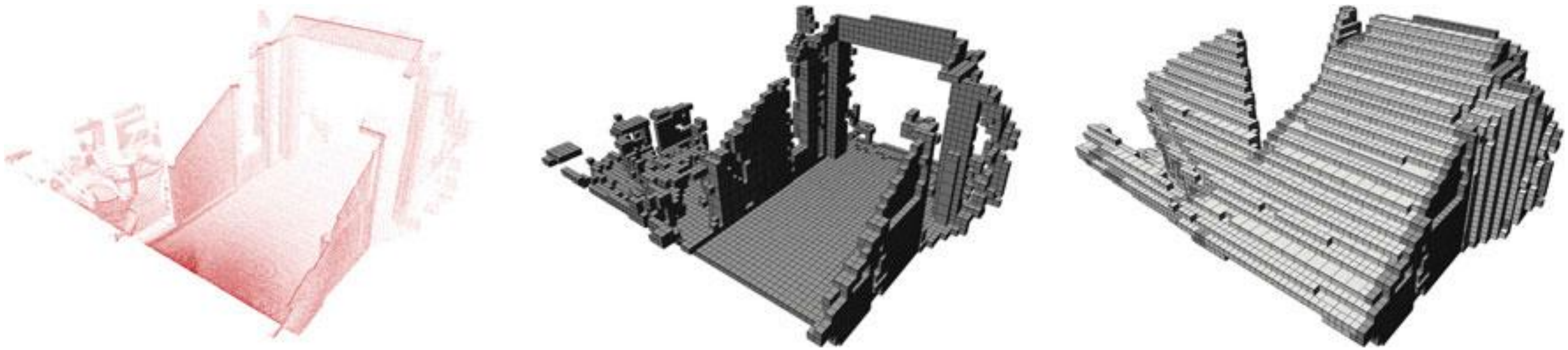
- Octomap, Occupancy map
  - "OctoMap: an efficient probabilistic 3D mapping framework based on octrees, Auton Robot (2013) 34:189–206"

$$P(n \mid z_{1:t}) = \left[1 + \frac{1 - P(n \mid z_t)}{P(n \mid z_t)} \frac{1 - P(n \mid z_{1:t-1})}{P(n \mid z_{1:t-1})} \frac{P(n)}{1 - P(n)}\right]^{-1}$$

$$L(n \mid z_{1:t}) = L(n \mid z_{1:t-1}) + L(n \mid z_t),$$

with

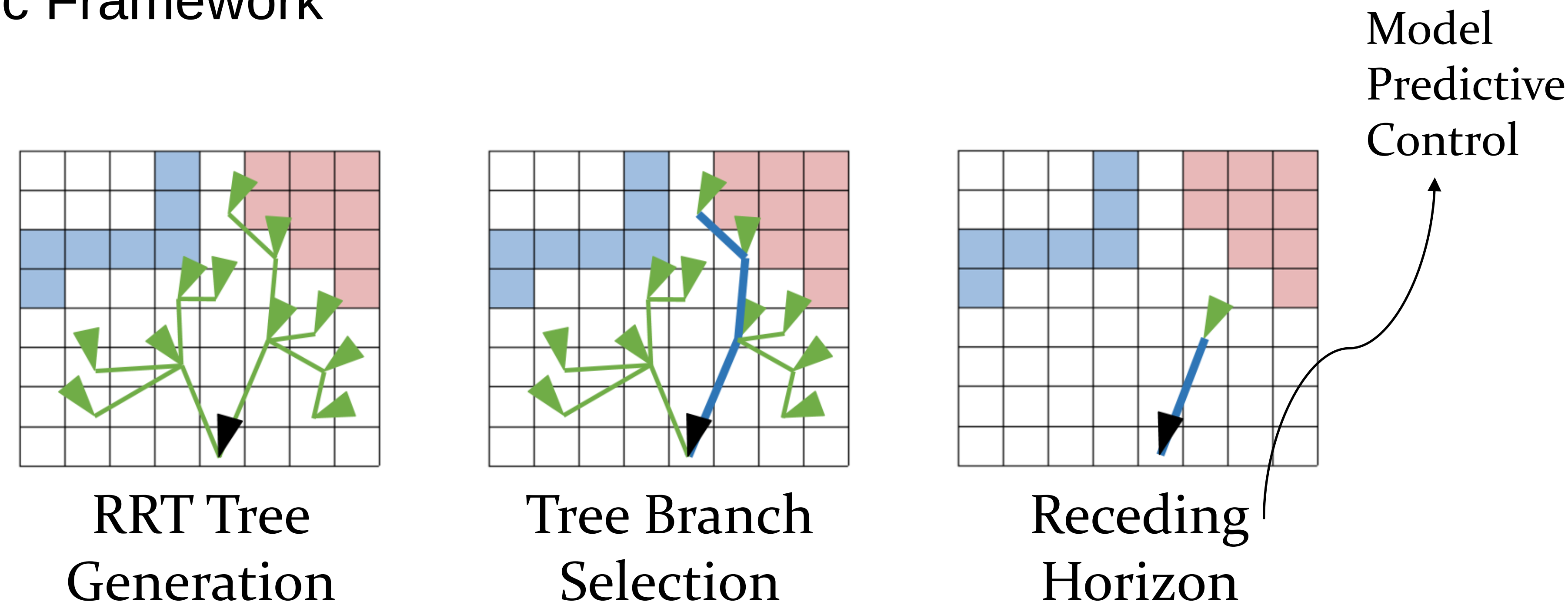
$$L(n) = \log\left[\frac{P(n)}{1 - P(n)}\right].$$



1. Receding Horizon "Next–Best–View" Planner for 3D Exploration

1. NBVP

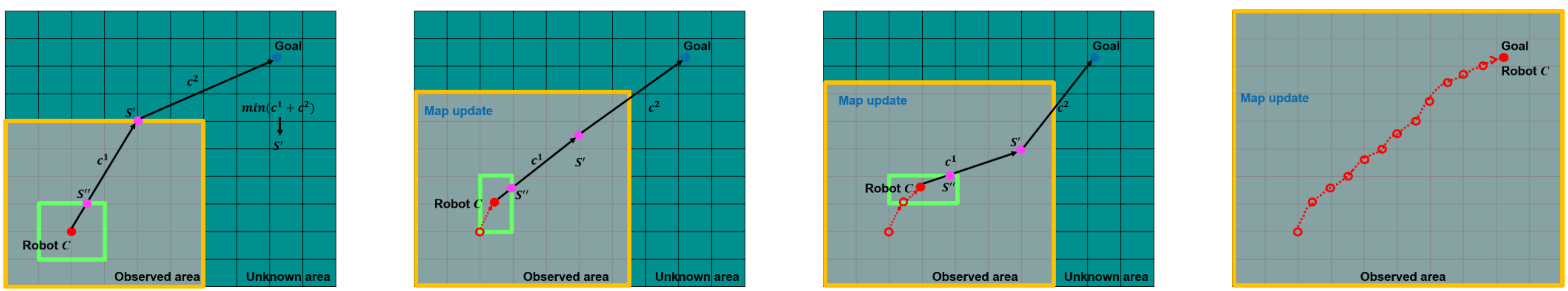
- Basic Framework



- Paths are only planned through known free space V_{free}, thus providing collision–free navigation

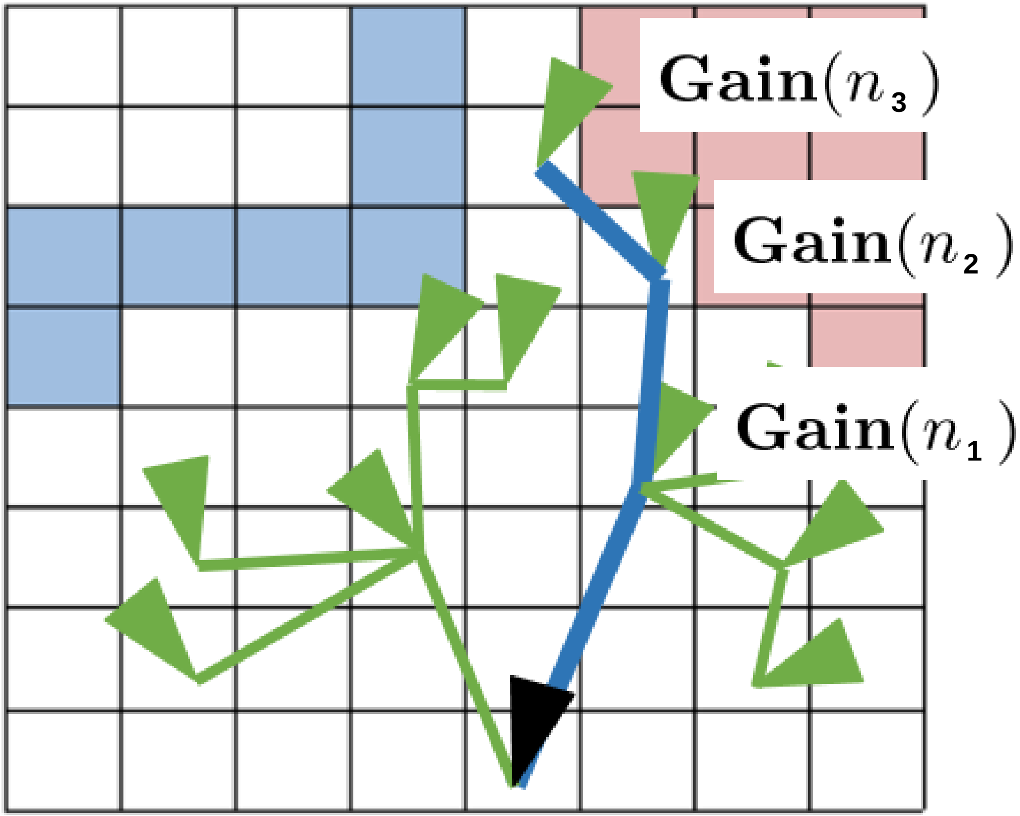
1. NBVP

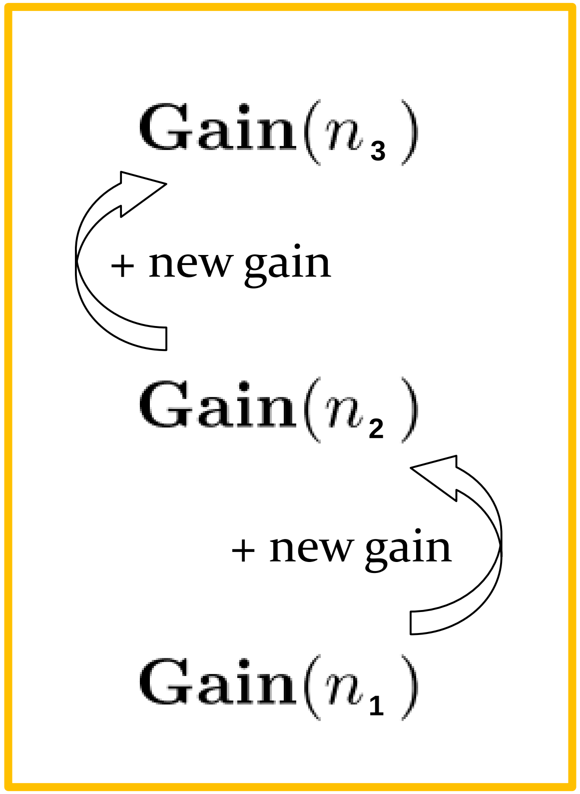
- Receding Horizon Planning (RHP)
  - Only the first waypoint is executed when the robot moves.
  - The map is updated as more grids are explored, and the path is re-planned if necessary.
  - Able to plan a smooth path where waypoints can be located on any position on the edge of grids without linear interpolation, which may not work for a cost function that includes nonlinear factors.



1. NBVP

- Summation of Gain – Selecting Best Qualified Tree





1. NBVP

Euclidean distance

$$c(\sigma_{k-1}^{k}) = \sqrt{(x_k - x_{k-1})^2 + (y_k - y_{k-1})^2 + (z_k - z_{k-1})^2}$$

- Quality - collected information gain

a path is given by $\sigma : \mathbb{R} \rightarrow \xi$
from ξ_{k-1} to ξ_k by $\sigma_{k-1}^{k}(s)$
path cost is $c(\sigma_{k-1}^{k})$

the world $\mathcal{M}$, visible and unmapped voxels from configuration ξ is denoted $\mathbf{Visible}(\mathcal{M}, \xi)$

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

tuning factor λ penalizing high path costs

$$\mathbf{ExtractBestPathSegment}(n_{best})$$

1. NBVP

sensor limitation is $d_{\max}^{\text{sensor}}$

$$d_{\max}^{\text{planner}} \leq d_{\max}^{\text{sensor}}$$

A lower $d_{\max}^{\text{planner}}$ ensures both robustness against suboptimal sensing conditions, as well as improved computational performance.

1. NBVP

Algorithm 1 Exploration Planner - Iterative Step

$\xi_0 \leftarrow$ current vehicle configuration
Initialize $\mathbb{T}$ with ξ_0 and, unless first planner call, also previous best branch
$g_{best} \leftarrow 0$ ▷ Set best gain to zero
$n_{best} \leftarrow n_0(\xi_0)$ ▷ Set best node to root
$N_{\mathbb{T}} \leftarrow$ Number of initial nodes in $\mathbb{T}$
while $N_{\mathbb{T}} < N_{\max}$ **or** $g_{best} = 0$ **do**
    Incrementally build $\mathbb{T}$ by adding $n_{new}(\xi_{new})$
    $N_{\mathbb{T}} \leftarrow N_{\mathbb{T}} + 1$
    if Gain$(n_{new}) > g_{best}$ **then**
        $n_{best} \leftarrow n_{new}$
        $g_{best} \leftarrow$ **Gain**(n_{new})
    if $N_{\mathbb{T}} > N_{TOL}$ **then**
        Terminate exploration
$\sigma \leftarrow$ **ExtractBestPathSegment**(n_{best})
Delete $\mathbb{T}$
return σ

1. NBVP

- Computational Complexity

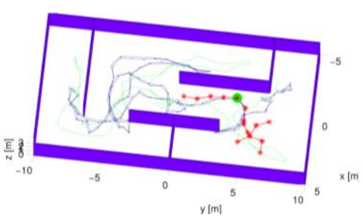
$$\mathcal{O}(\underbrace{N_{\mathbb{T}} \log(N_{\mathbb{T}})}_{\text{RRT complexity}} + \underbrace{N_{\mathbb{T}}/r^3 \log(V/r^3)}_{\text{Occupancy map complexity with } 1/r^3 \text{ scale}} + \underbrace{N_{\mathbb{T}}(d_{\max}^{\text{planner}}/r)^4 \log(V/r^3)}_{\text{Gain computation complexity}})$$

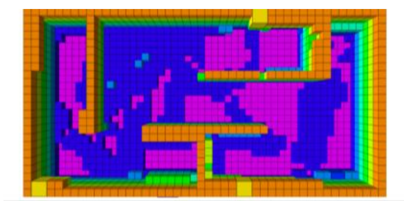
V: volume to explore
r: resolution of occupancy map
$\boldsymbol{d_{max}^{planner}}$: *sensor range*
$\boldsymbol{N_T}$: *number of nodes in the tree*

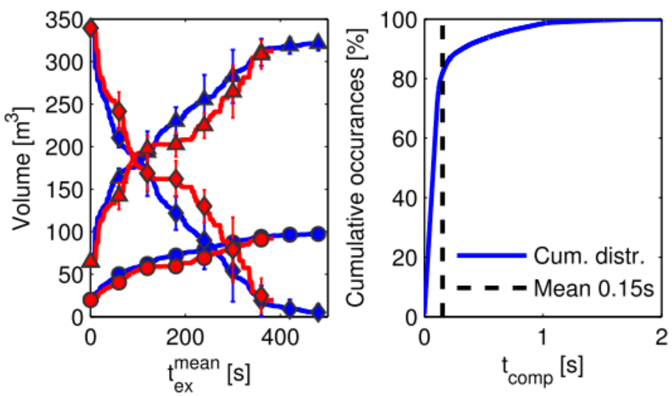
1. NBVP

Indoor Simulation Experiment

Parameter	Value	Parameter	Value
Area	20x10x3m	Map resolution r	0.4m
$v_{\max}$	0.2m/s	$\dot{\psi}_{\max}$	0.75rad/s
FoV	$[60, 90]^\circ$	Mounting pitch	15°
$d_{\max}^{\text{planner}}$	2m	$d_{\max}^{\text{sensor}}$	5m
λ	0.5	RRT max edge length	1m
$N_{\max}$	15	Collision box	0.5x0.5x0.3m



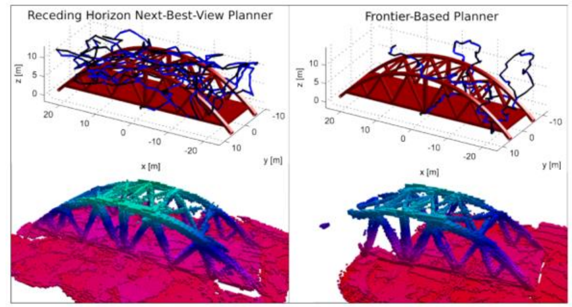


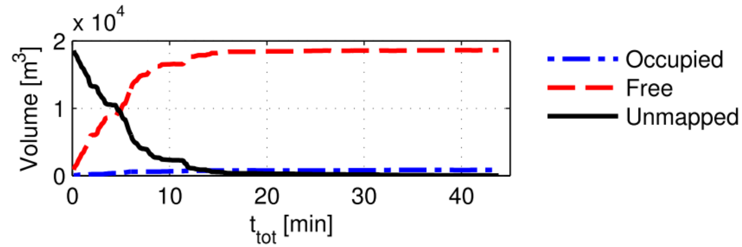


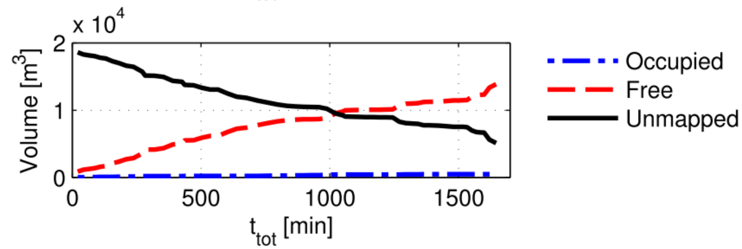
occupied o, **free** △ and **unmapped** ◊ volumes.

Bridge Simulation Experiment

Parameter	Value	Parameter	Value
Area	50x26x14m	Map resolution r	0.25m
$v_{\max}$	0.5m/s	$\dot{\psi}_{\max}$	0.75rad/s
FoV	$[60, 90]^\circ$	Mounting pitch	15°
$d_{\max}^{\text{planner}}$	2m	$d_{\max}^{\text{sensor}}$	10m
λ	0.2	RRT max edge length	3m
$N_{\max}$	30	Collision box	0.5x0.5x0.3m







1. NBVP

- Real World Experiment

Parameter	Value	Parameter	Value
Area	9x7x2m	Map resolution r	0.2m
$v_{\max}$	0.25m/s	$\dot{\psi}_{\max}$	0.3rad/s
FoV	$[60, 90]^\circ$	Mounting pitch	15°
$d_{\max}^{\text{planner}}$	1m	$d_{\max}^{\text{sensor}}$	5m
λ	0.5	RRT max edge length	1.5m
$N_{\max}$	20	Collision box	1.2x1.2x0.5m

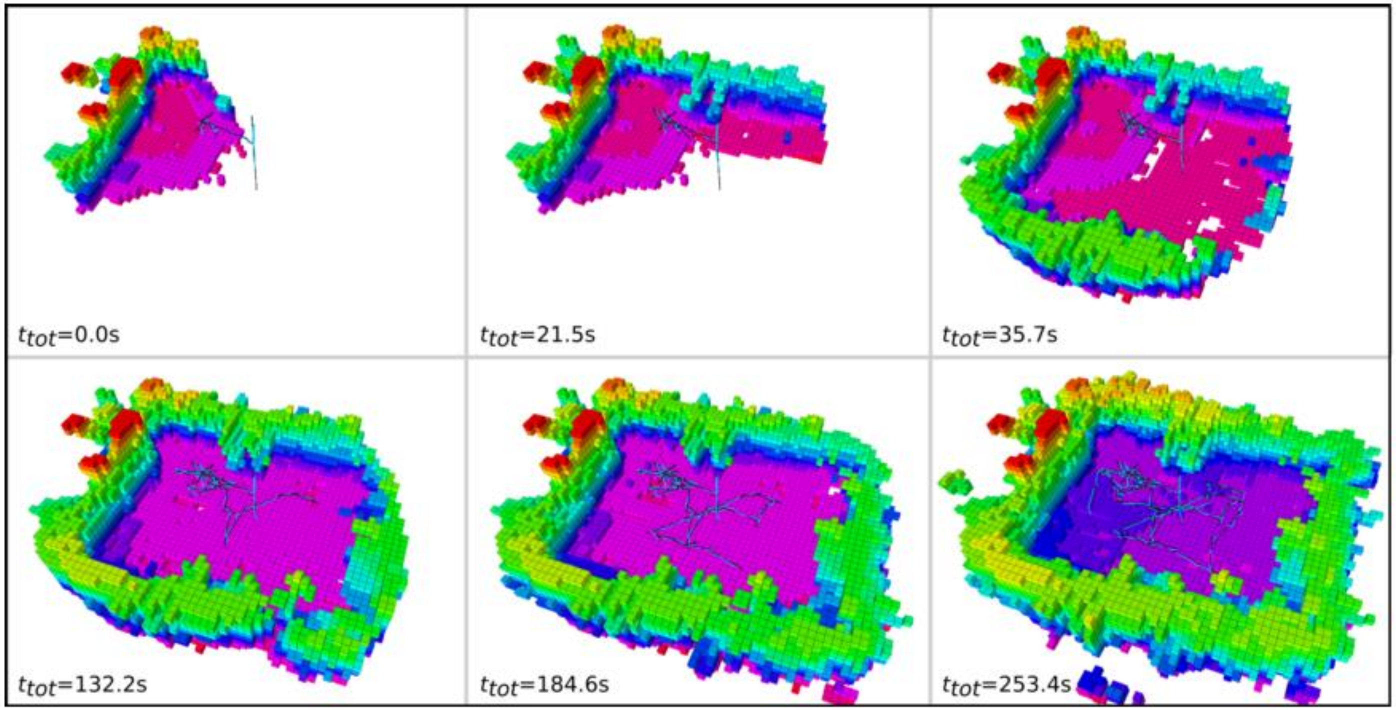
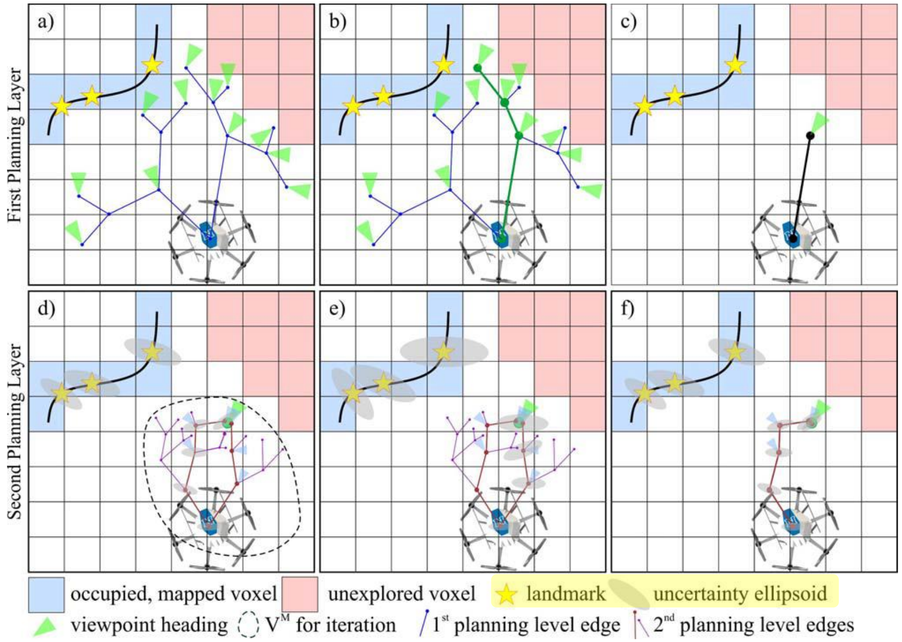


Fig. 8: The exploration experiment in a closed room is depicted. The colored voxels represent occupied parts of the occupancy map (colored according to height) while the computed path is given in black and the vehicle response in light blue. The initial phase of the exploration mission is dominated by yawing motions to maximize exploration without traveling large distances. Subsequently the MAV explores regions further away, to eventually accomplish its mission.

2. Uncertainty–aware Receding Horizon Exploration and Mapping using Aerial Robots

2. UEP

- Key requirements for the VIO to perform robustly
  - must **reobserve landmarks with good confidence**
  - better to **follow trajectories that appropriately excite the inertial sensors**



- This has two effects
  - **improving the location estimate of the features**
  - **improving the pose estimate of the robot** due to the statistical correlations that link the vehicle to the features.

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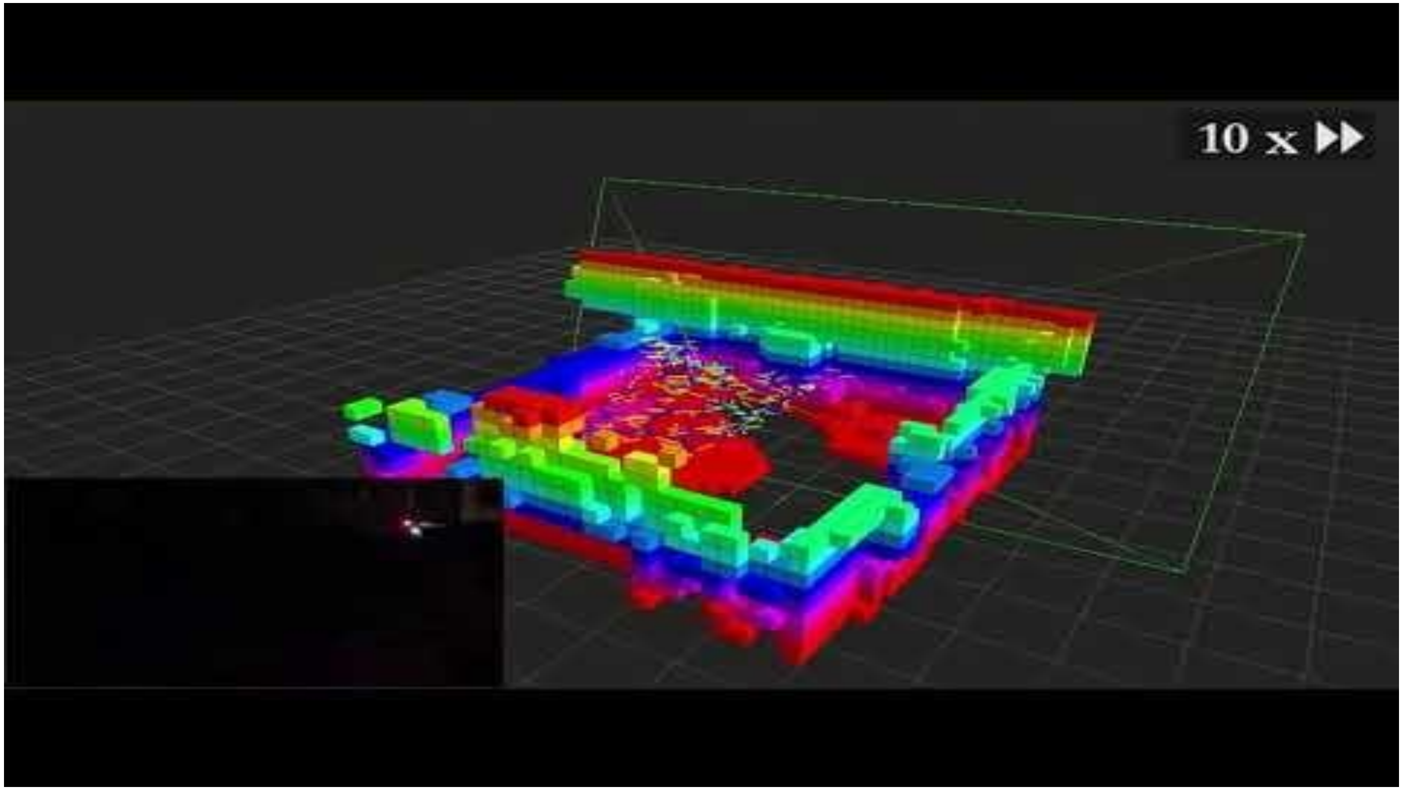
2. UEP

- Especially when the robot explores an unknown environment, new features are initialized into the map.

- This imposes the **need to reobserve previous features** in order to **reduce the growth in localization** and **mapping error**

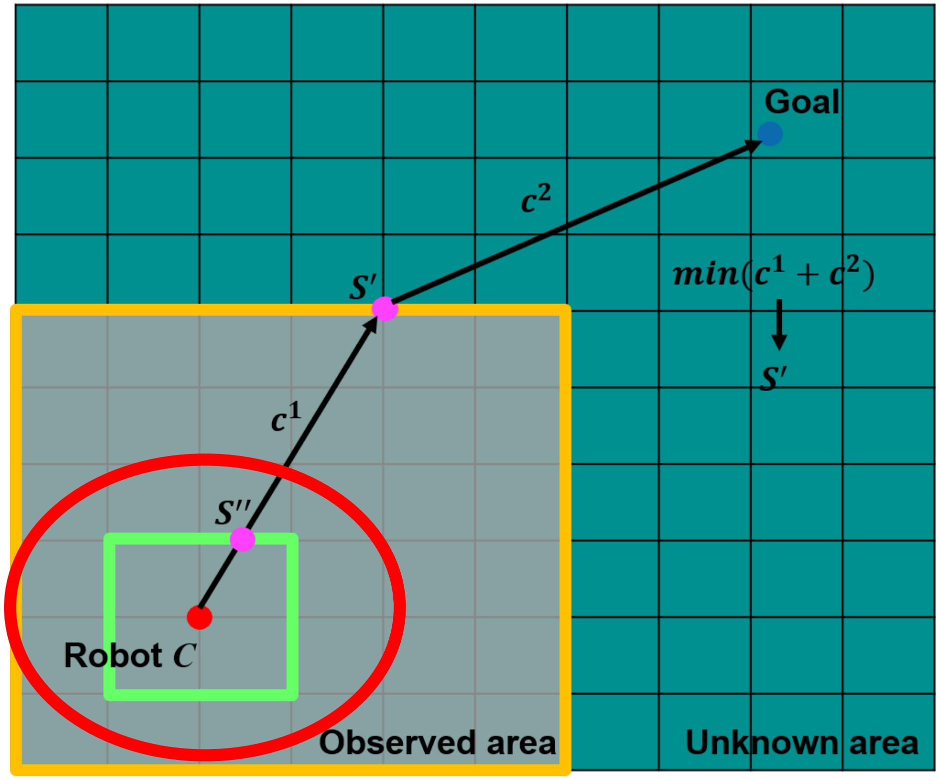
2. UEP

- Two–Step Planner
  - First, receding horizon planner
  - Second, belief space–based planner



2. UEP

- Two–Step Planner
  - S'' has selected by receding horizon planner
  - S'' be the goal for nested second planner



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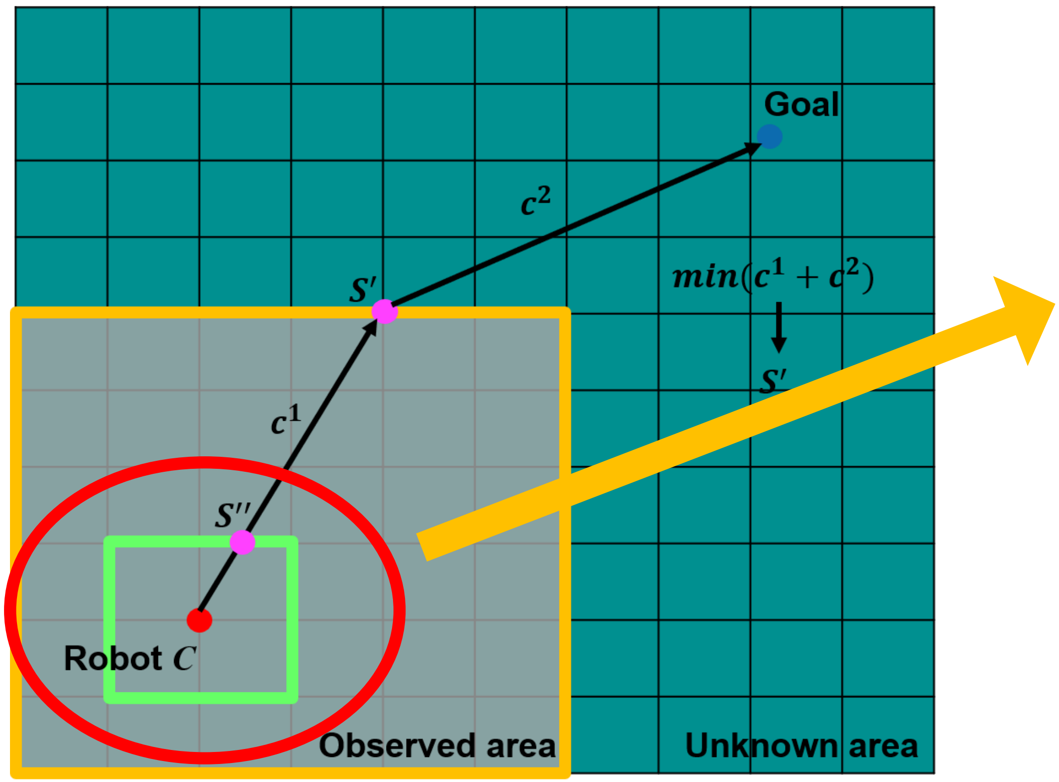

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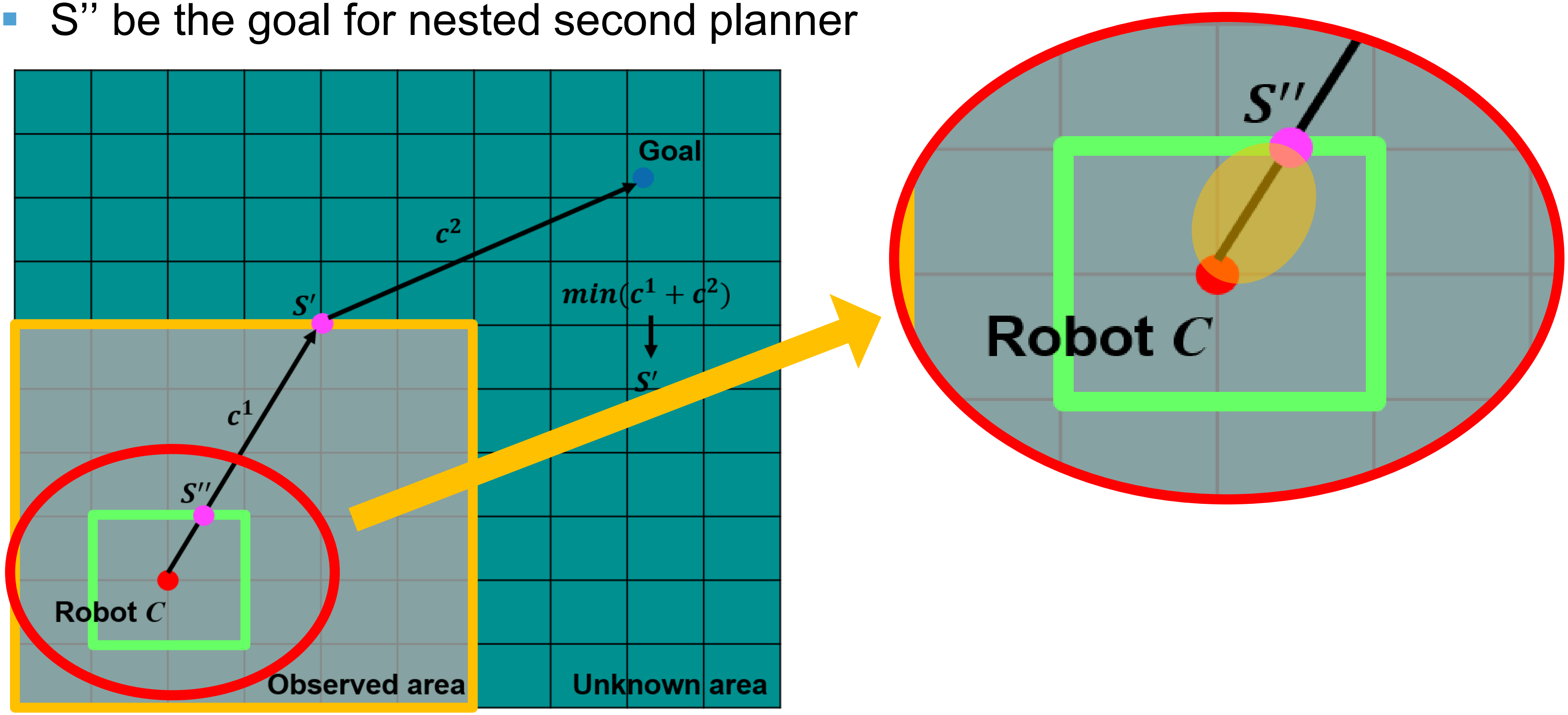
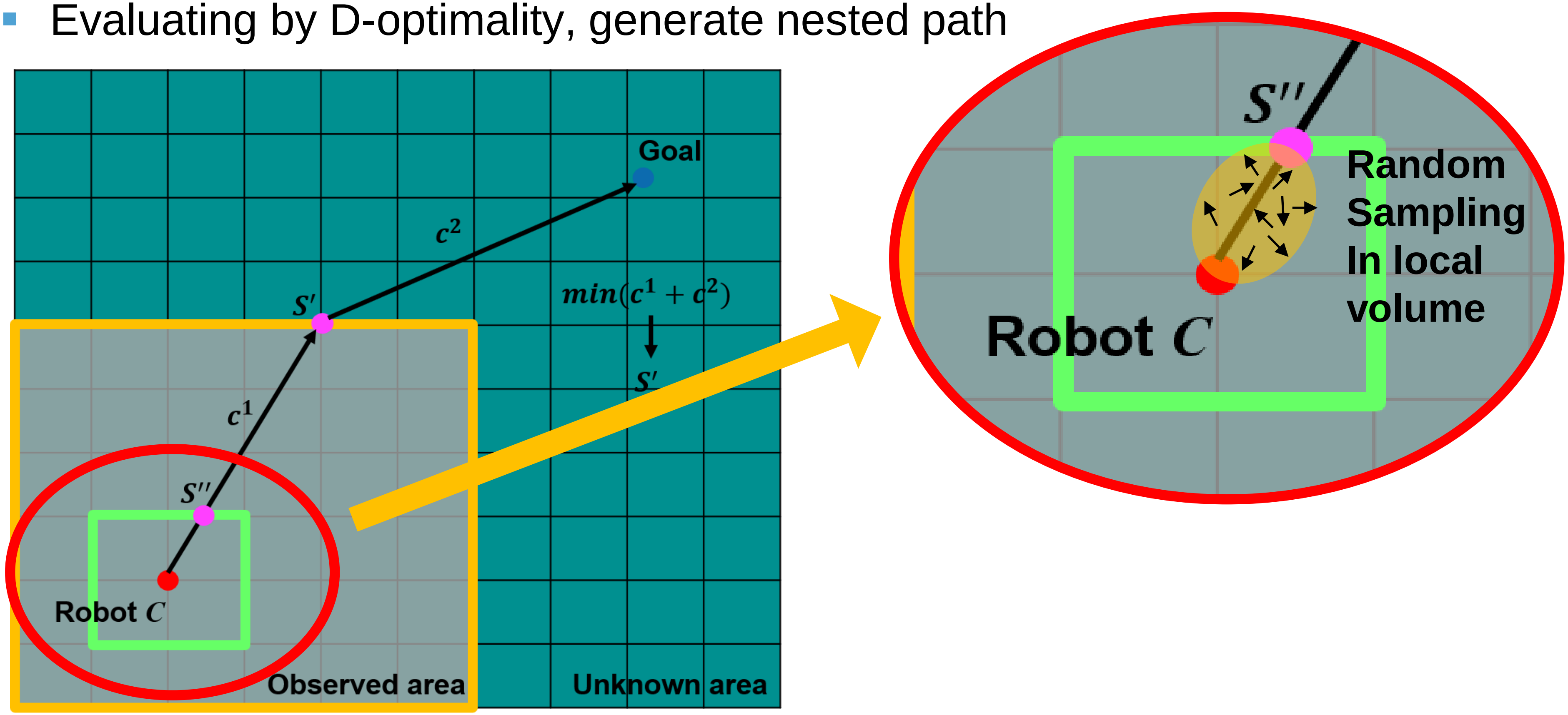


2. UEP

- Two–Step Planner
  - Make a local volume and sample the random tree
  - Evaluating by D-optimality, generate nested path



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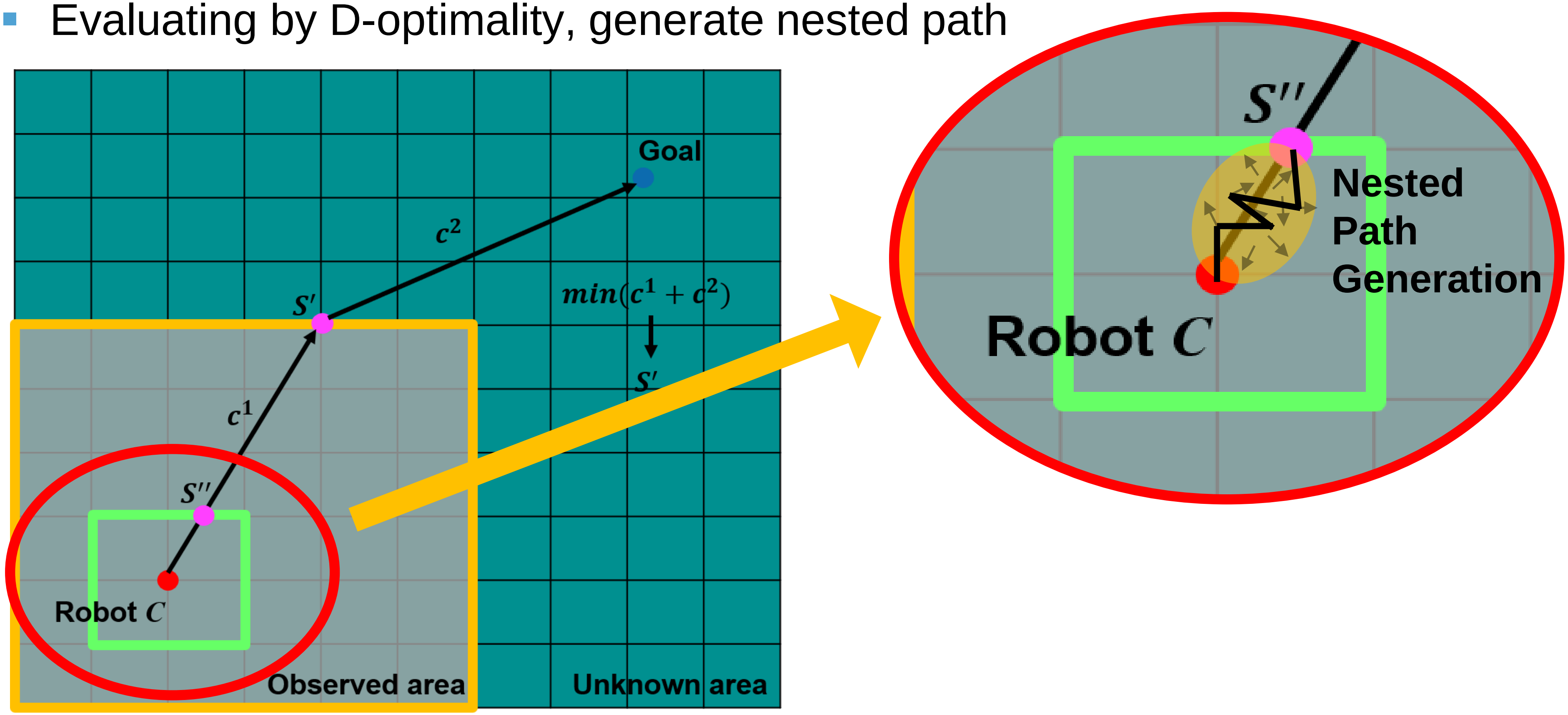


2. UEP

Algorithm 1 Proposed Planner - Iterative Step

$\xi_0 \leftarrow$ current vehicle configuration
Initialize $\mathbb{T}^E$ with ξ_0
$g^E_{best} \leftarrow 0$ ▷ Set best exploration gain to zero
$n^E_{best} \leftarrow n_0(\xi_0)$ ▷ Set best exploration node to root
$N^E_{\mathbb{T}} \leftarrow$ Number of initial nodes in $\mathbb{T}^E$
while $N^E_{\mathbb{T}} < N^E_{\max}$ **or** $g^E_{best} = 0$ **do**
  Incrementally build $\mathbb{T}^E$ by adding $n^E_{new}(\xi_{new})$
  $N^E_{\mathbb{T}} \leftarrow N^E_{\mathbb{T}} + 1$
  if $\mathbf{ExplorationGain}(n^E_{new}) > g^E_{best}$ **then**
    $n^E_{best} \leftarrow n^E_{new}$
    $g^E_{best} \leftarrow \mathbf{ExplorationGain}(n^E_{new})$
  end if
  if $N^E_{\mathbb{T}} > N^E_{TOL}$ **then**
    Terminate planning
  end if
end while
$\sigma^E_{RH}, n^E_{RH}, \xi_{RH} \leftarrow \mathbf{ExtractBestPathSegment}(n^E_{best})$
$\mathbb{S}_{\xi_{RH}} \leftarrow \mathbf{LocalSet}(\xi_{RH})$
Propagate robot belief along σ^E_{RH}
$\alpha \leftarrow 1$ ▷ number of admissible paths
$g^M_\alpha \leftarrow \mathbf{BeliefGain}(\sigma^E_{RH})$
$g^M_{best} \leftarrow g^M_\alpha$ ▷ straight path belief gain
$\sigma^M_{best} \leftarrow \sigma^M_{RH}$ ▷ Set best belief path
while $N^M_{\mathbb{T}} < N^M_{\max}$ **or** $\mathbb{V}(\mathbb{T}^M) \cap \mathbb{S}_{\xi_{RH}} = \emptyset$ **do**
  Incrementally build $\mathbb{T}^M$ by adding $n^M_{new}(\xi_{new})$
  Propagate robot belief from current to planned vertex
  if $\xi_{new} \in \mathbb{S}_{\xi_{RH}}$ **then**
    Add new vertex n^M_{new} at ξ_{RH} and connect
    $\alpha \leftarrow \alpha + 1$
    $\sigma^M_\alpha \leftarrow \mathbf{ExtractBranch}(n^M_{new})$
    $g^M_\alpha \leftarrow \mathbf{BeliefGain}(\sigma^M_\alpha)$
    if $g^M_\alpha < g^M_{best}$ **then**
      $\sigma^M \leftarrow \sigma^M_\alpha$
      $g^M_{best} \leftarrow g^M_\alpha$
    end if
  end if
end while
return σ^M

2. UEP

- Gain Function(1st planner)

$$\textbf{ExplorationGain}(n_k^E) = \textbf{ExplorationGain}(n_{k-1}^E) + \textbf{VisibleVolume}(\mathcal{M}, \xi_k)\exp(-\lambda c(\sigma_{k-1,k}^E)) + \textbf{ReobservationGain}(\mathcal{M}, \mathcal{P}, \xi_k)\exp(-\lambda c(\sigma_{k-1,k}^E))$$

$\textbf{VisibleVolume}(\mathcal{M}, \xi)$

$c(\sigma_{k-1,k}^E)$ is the length of the path

$\textbf{ReobservationGain}(\mathcal{M}, \mathcal{P}, \xi)$ their volume weighted by $(1 - \mathcal{P}(m))$

P(m) := probability of occupied voxel

2. UEP

- Gain Function(2nd planner)

$$\textbf{BeliefGain}(\sigma_\alpha^M) = D_{opt}(\sigma_\alpha^M)$$

$$D_{opt}(\sigma^M) = \exp(\log([\det(\boldsymbol{\Sigma}_{p,f}(\sigma^M)]^{1/(l_p+l_f)}))$$

$\Sigma_{p,f}$: Derived pose and tracked landmarks covariance matrix of robot and feature state, in the paper they used EKF covariance which is used with ROVIO image patch

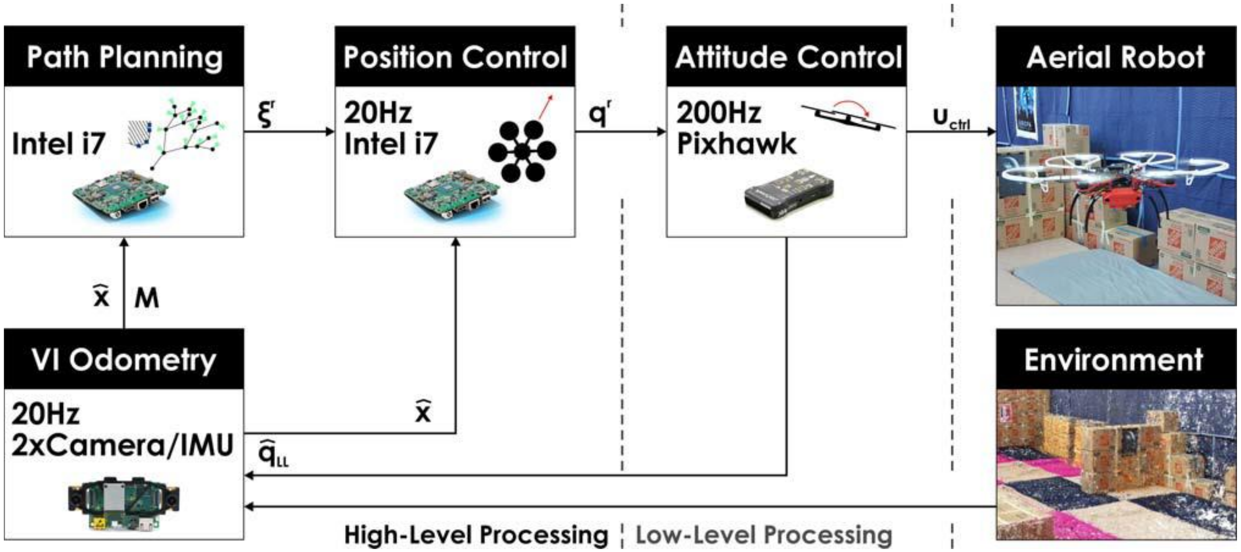
l_p, l_f : Dimensions of pose, robot state, features state

2. UEP

- Computational Complexity

RRT construction	Collision checking
$\mathcal{O}(N_{\mathbb{T}}^{S}\log(N_{\mathbb{T}}^{S})),\ S \rightarrow E, M$	$\mathcal{O}(N_{\mathbb{T}}^{S}/r^{3}\log(V^{E}/r^{3})),\ S \rightarrow E, M$
1^{st} planning level gain computation	
$\mathcal{O}(N_{\mathbb{T}}^{E}(d_{\max}^{\text{planner}}/r)^{4}\log(V^{E}/r^{3}))$	
2^{nd} planning level gain computation	
$\mathcal{O}(N_{\mathbb{T}}^{M}(d_{\max}^{\text{sensor}}/r)^{4}\log(V^{E}/r^{3})l_{f} + n_{M}(l_{s}^{2.4} + l_{f}^{2}) + n_{M}(l_{p} + l_{f}))$	

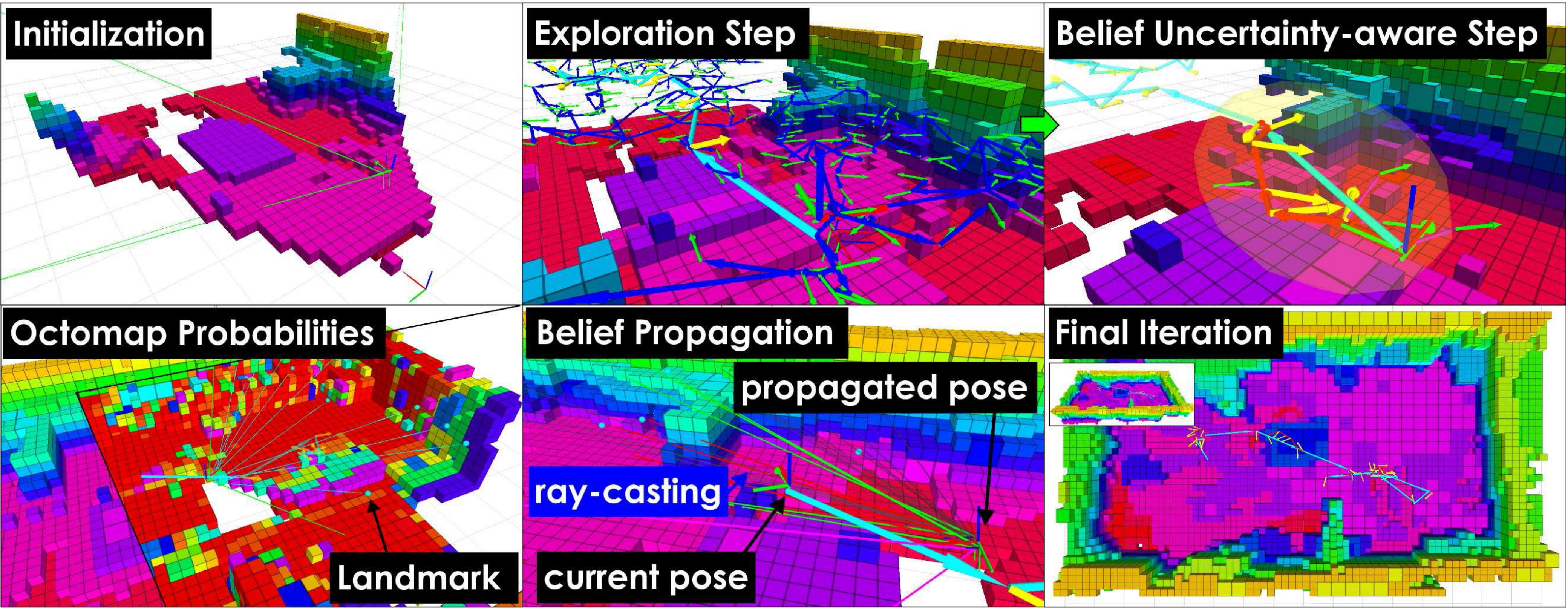
2. UEP



EXPERIMENTAL PARAMETERS

Parameter	**Value**	**Parameter**	**Value**
Volume	12x6.5x2m	Map resolution r	0.2m
$v_{\max}$	0.75m/s	$\dot{\psi}_{\max}$	$\pi/4$rad/s
FoV	$[60, 90]^\circ$	Mounting pitch	13.5°
$d_{\max}^{\text{planner}}$	3.5m	$d_{\max}^{\text{sensor}}$	7.5m
λ	0.35	ℓ_E	1.5m
$N_{\max}^E$	250	ℓ_M	0.375m
$N_{\max}^M$	50	Collision box	1.2x1.2x0.6m
δ	1.5	l_f	25
T_s	0.1	p_{thres}	0.97

2. UEP


Initialization
Exploration Step
Belief Uncertainty-aware Step
Octomap Probabilities
Landmark
Belief Propagation
propagated pose
ray-casting
current pose
Final Iteration

2. UEP

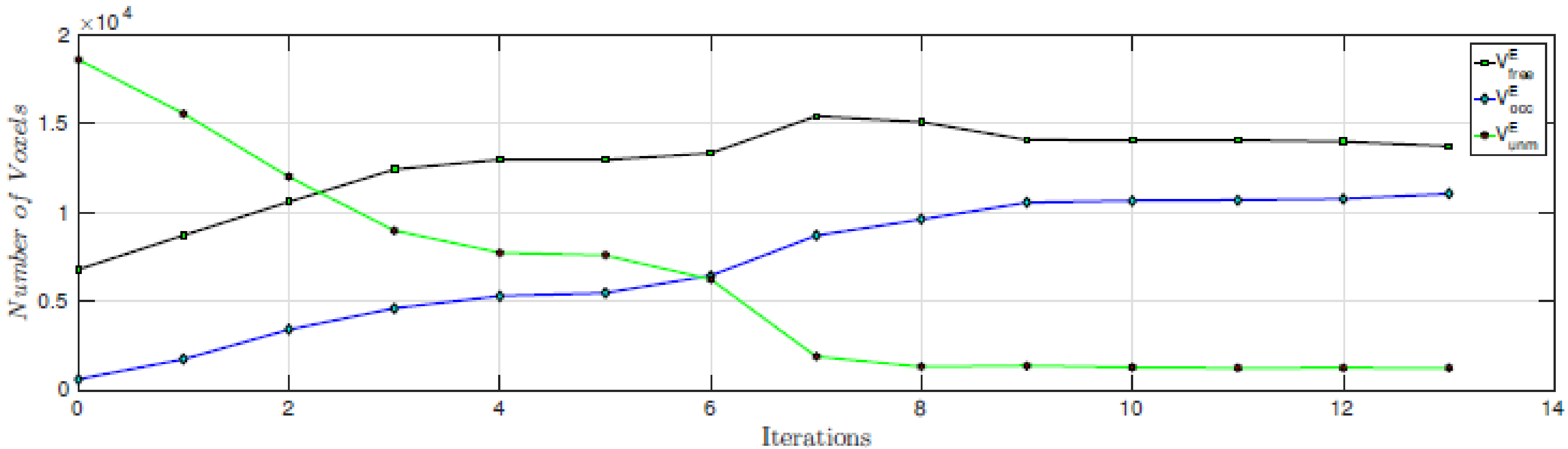


Fig. 6. Rate of exploration per iteration (upper plot, black line for explored free space, blue for explored occupied space and green for the unmapped space), best 2 D-opt gain calculations for the second, nested, planning layer

3. Conclusion

Index		NBVP	UEP
Similar Point	Space Representation	Occupancy map(Octomap)	
	Path Randomness	RRT based sampling, Frequent back & forth movement	
Different Point	Considering Localization	No	YES(reobservation gain)
	Path Complexity	Low	High(second path planner)
	Exploration Time	Better than FE	Worse time performance

4. Quiz

1) NBV-planner have visibility element on gain function. (T/F)

2) UEP is short name of 'Unsaturation Aware Planning'. (T/F)

Thank you