CS491/691: Introduction to Aerial Robotics

Topic: Sampling-based Autonomous Exploration

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Real-life is 3D, Complex, Possibly unknown

Known Model to Compute Global Inspection Path

Unknown Model – execute Autonomous Exploration

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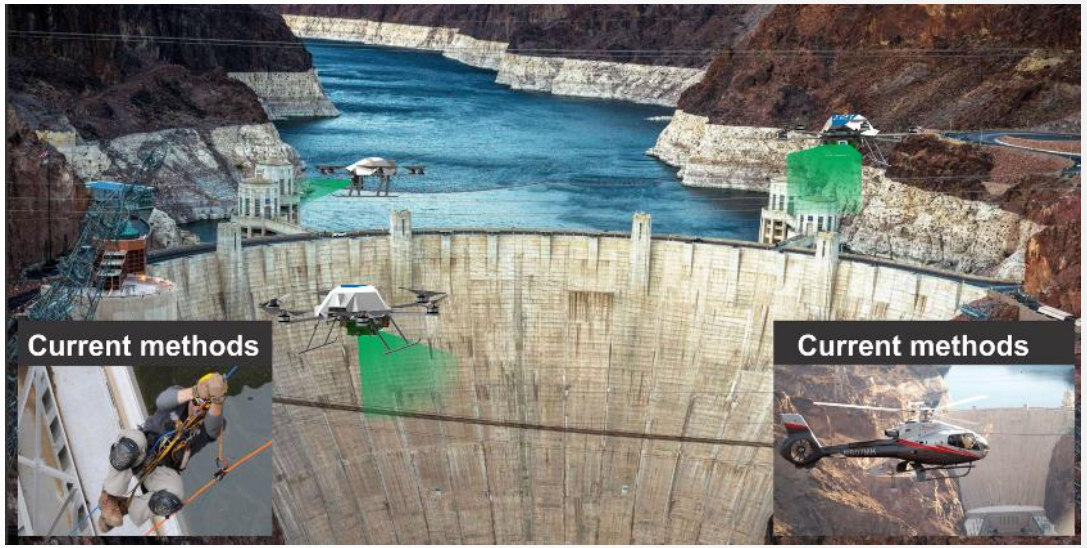
Unknown Model – execute Autonomous Exploration

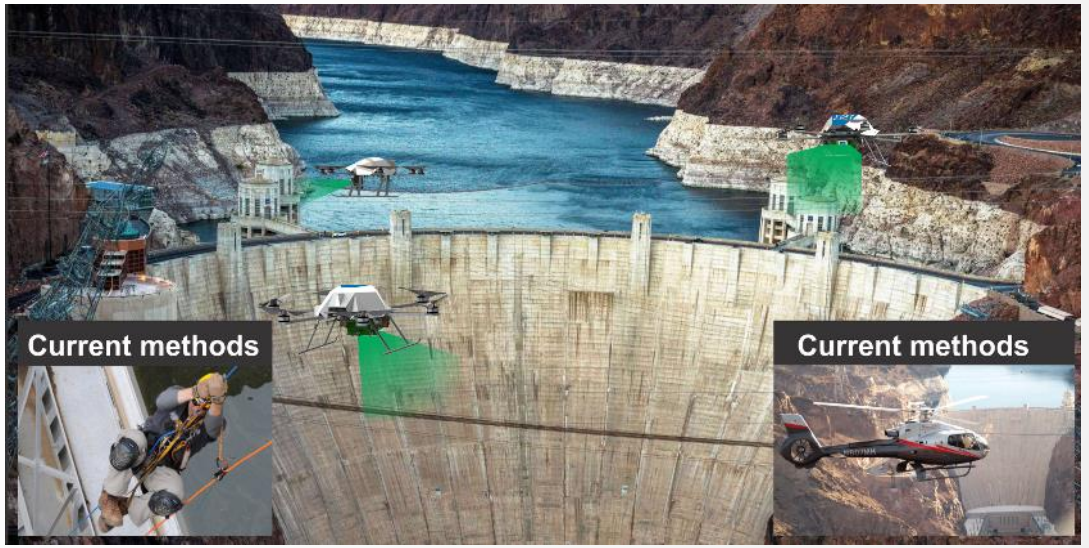
What is exploration?

- How robots map an unknown area in order to determine the conditions and characteristics of the environment (typically: to map it).



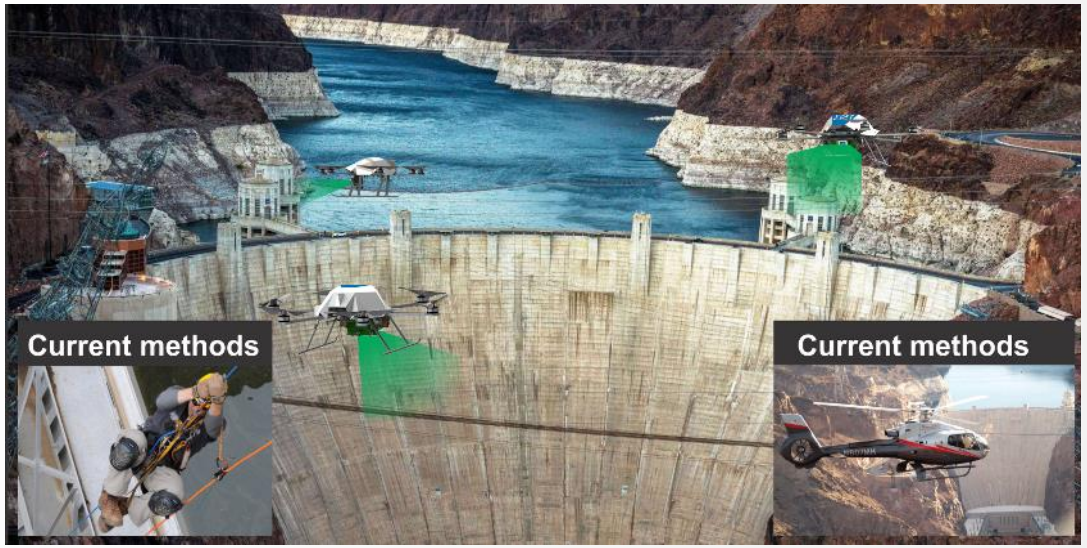
Exploration is different than Coverage

- Coverage problems assume that the map is known and the objective is to optimally cover and/or possibly identify targets of interest in it.
- Exploration problems deal with how to map a previously unknown world!



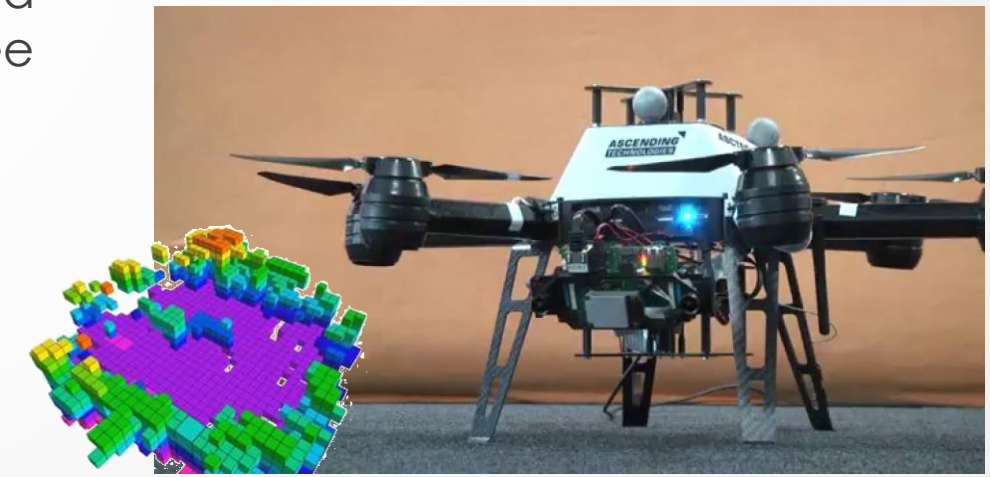
Applications of Autonomous Exploration

- Infrastructure monitoring and maintenance
- Rapid support of search and rescue operations
- Surveillance and reconnaissance
- Operation in any environment not suitable for human operators



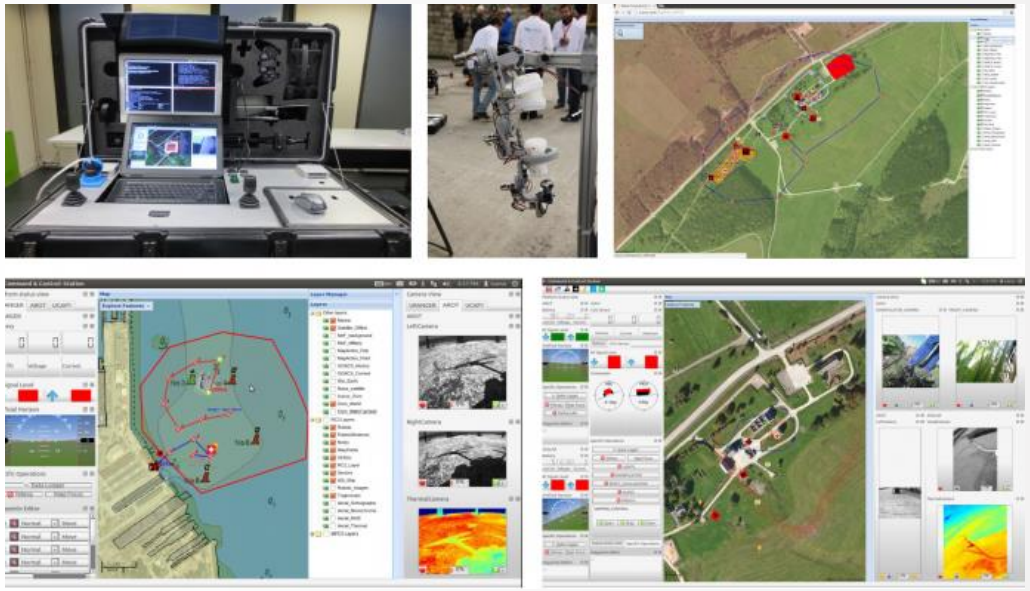
Methods for Autonomous Exploration

- **Human-directed:** no robot-autonomy. The human is teleoperating the robot.
- **Random:** select viewpoints based on a purely random approach.
- **Frontier-based:** select viewpoints at the frontier of the explored space.
- **Sampling-based Receding Horizon Next-Best-View Exploration:** select viewpoints in a receding horizon fashion over a random tree of viewpoints.



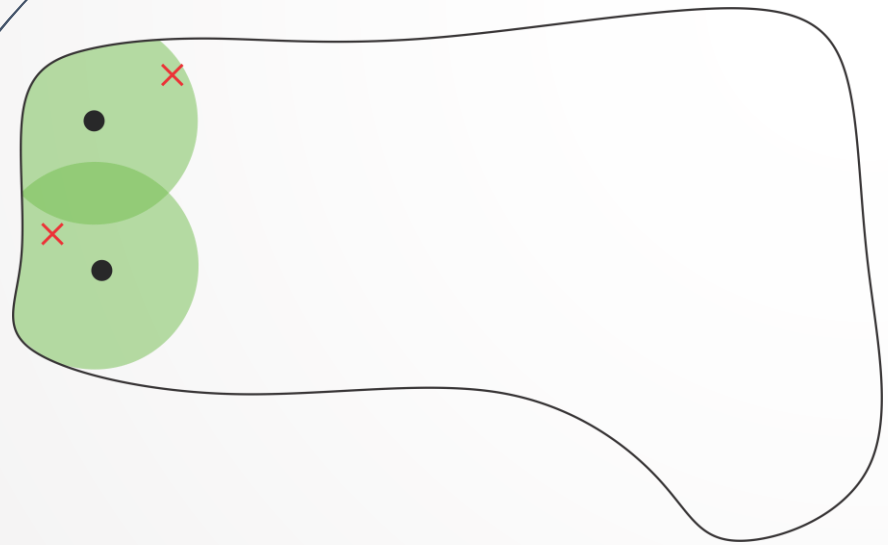
Human-directed

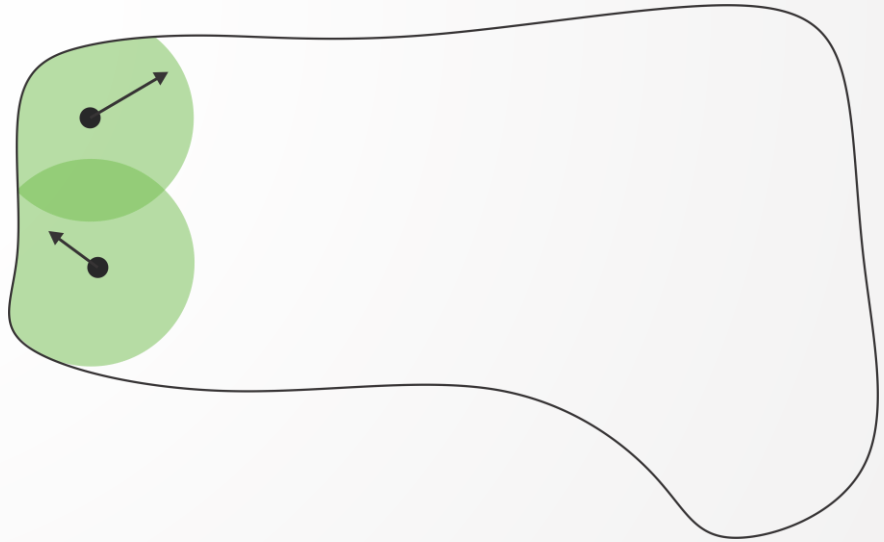
- A graphical user interface enables humans to direct robots to explore the unknown environment.
- An incrementally built map of the explored space is typically displayed to the user.



Random Exploration

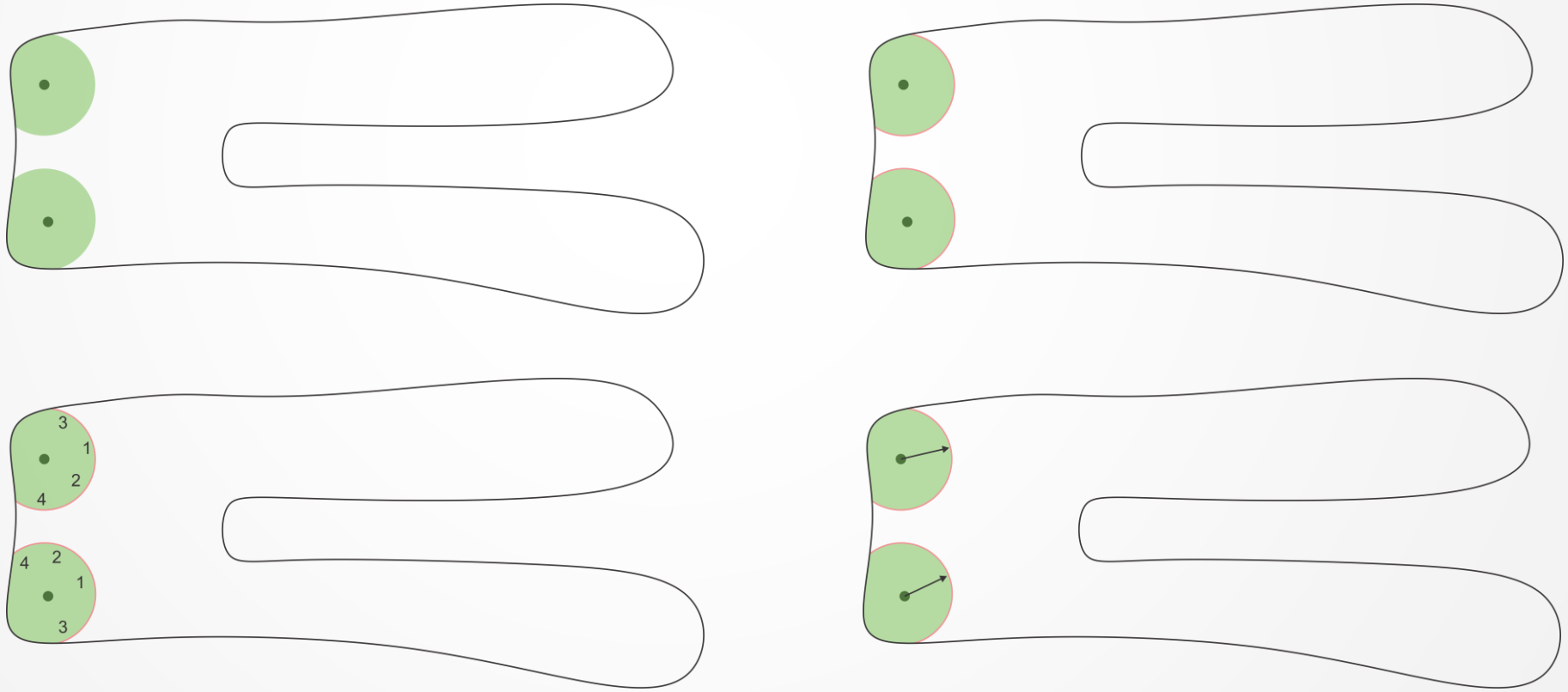
- Explore **random configurations/viewpoints** that are within a given distance from each robot.
- Base metric for the performance of any exploration algorithm.
- Smarter version of the algorithm only picks points in unexplored area.





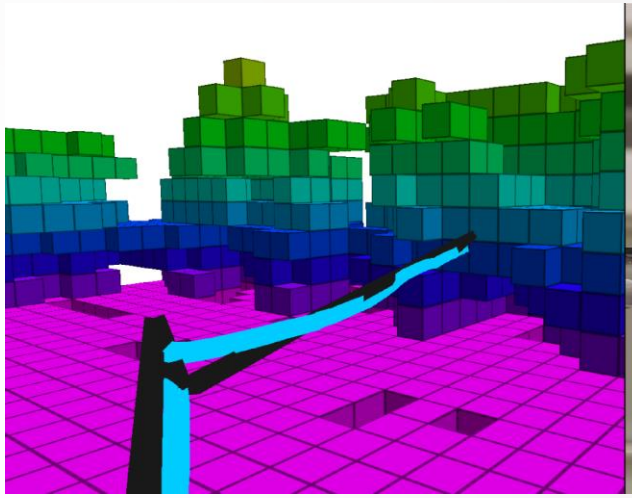
Frontier-based Exploration

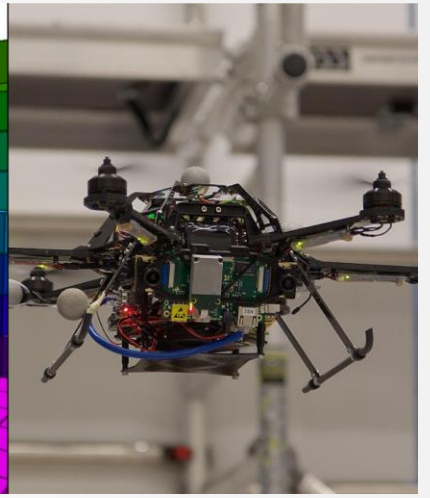
- Explore the areas where known space ends and unknown space begins (**frontiers**).
- Prioritize the different frontiers depending on their size, distance from robots, proximity to obstacles, and distance from other frontiers. What is a good frontier?

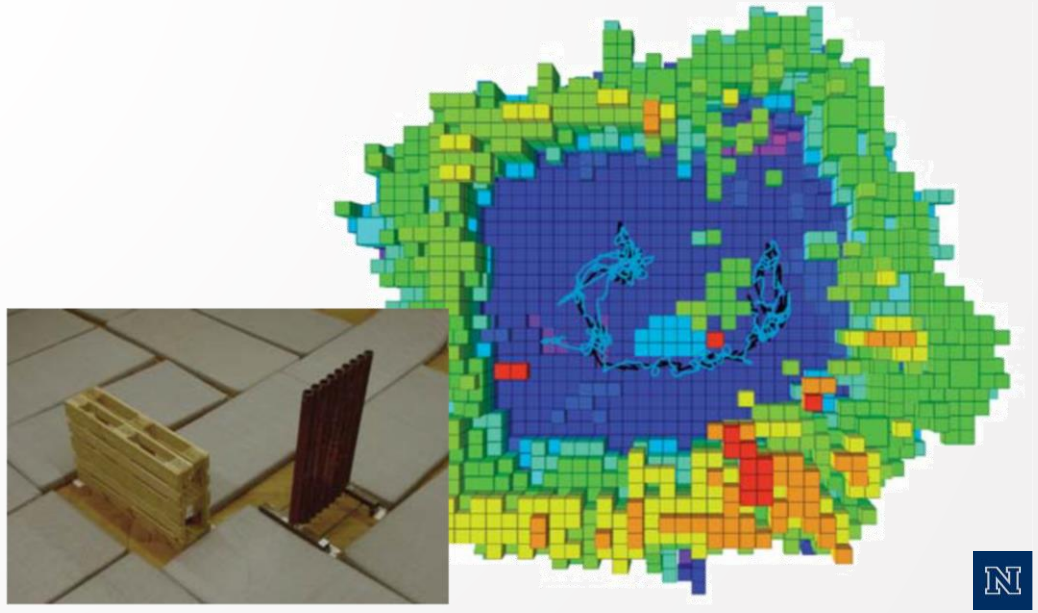


Receding Horizon Next-Best-View Exploration

- Rapid exploration of unknown environments.
- Define **sequences of viewpoints based on vertices sampled using random trees**.
- Select the path with the best sequence of best views.
- Execute only the first step of this best exploration path.
- Repeat the whole process in a receding horizon fashion.







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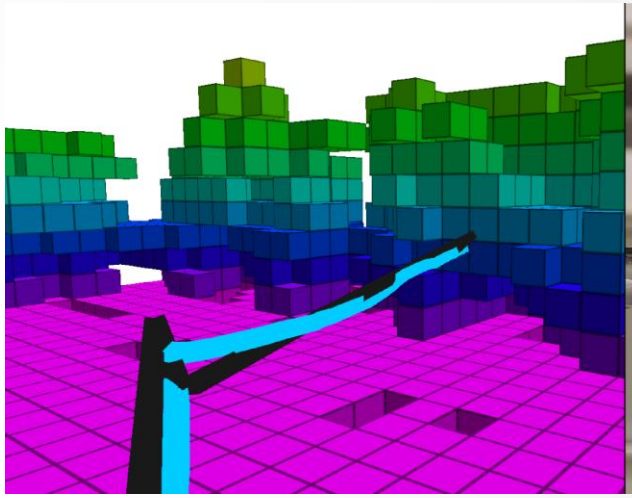
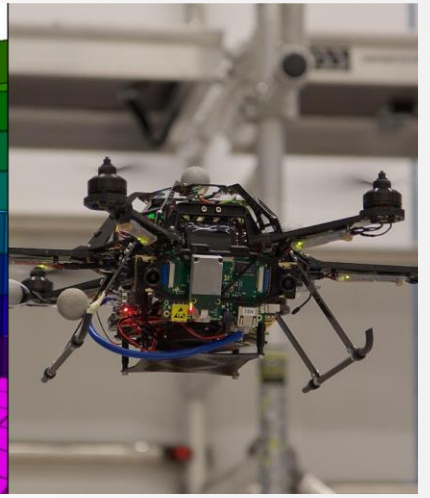
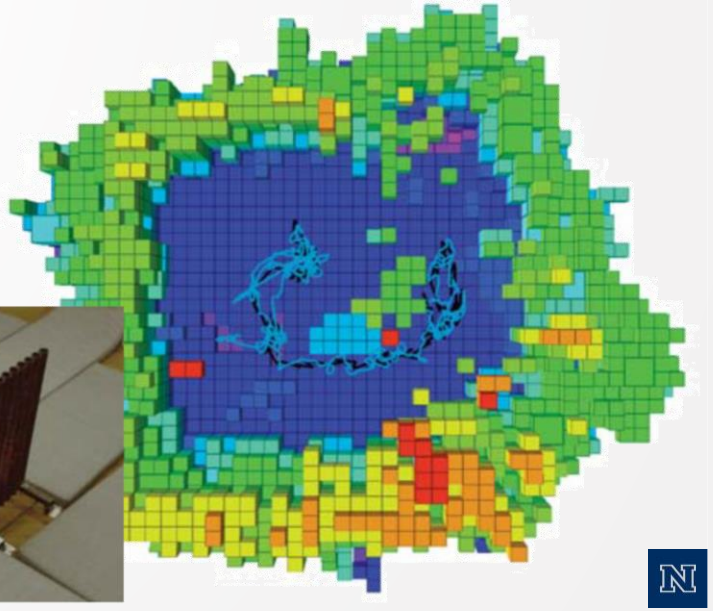
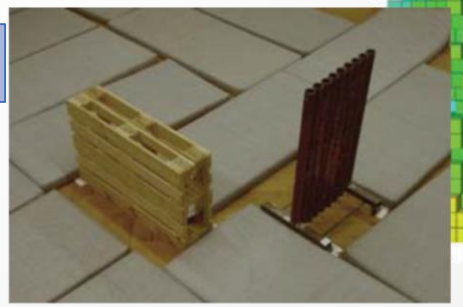








We will specifically focus on that method.

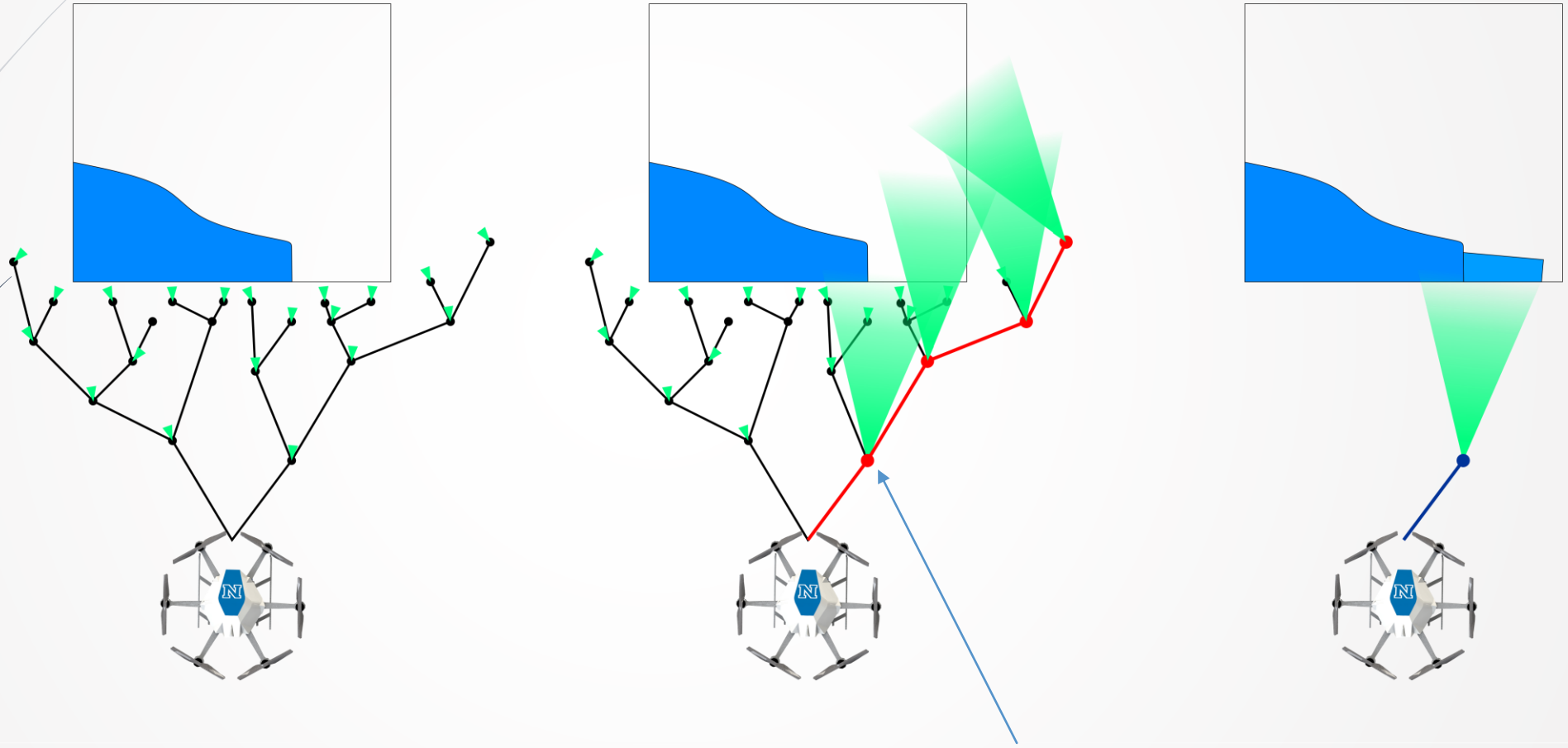
The Exploration path planning problem

Problem Definition

The exploration path planning problem consists in exploring a bounded 3D space $V \subset \mathbb{R}^3$. This is to determine which parts of the initially unmapped space $V_{unm} = V$ are free $V_{free} \subset V$ or occupied $V_{occ} \subset V$. The operation is subject to vehicle kinematic and dynamic constraints, localization uncertainty and limitations of the employed sensor system with which the space is explored.

- 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 is denoted as V_{res}. The problem is considered to be fully solved when $V_{free} \cup V_{occ} = V \backslash V_{res}$.
- Due to the nature of the problem, a suitable path has to be computed online and in real-time, as free space to navigate is not known prior to its exploration.

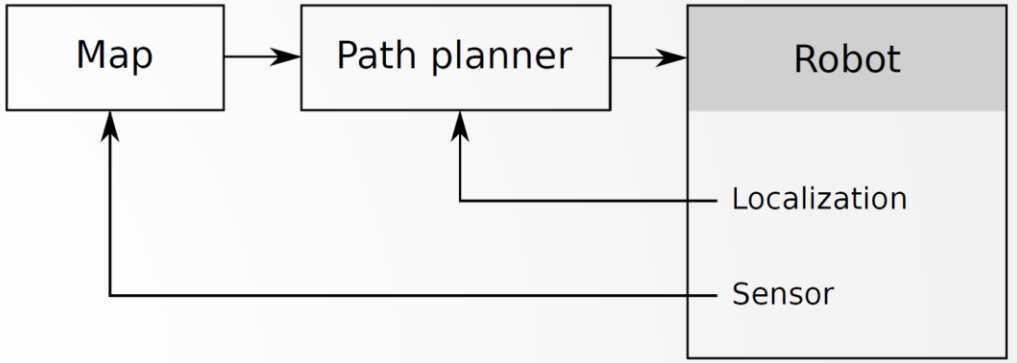
RH-NBVP Functional Principle



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

RH-NBVP Approach

- **Environment representation:** Occupancy Map dividing space V into $m \in M$ cubical volumes (voxels) that can be marked either as free, occupied or unmapped.
- Array of voxels is saved in an octree structure to enable computationally efficient access and search.
- Paths are planned only within the free space V_{free} and collision-free point-to-point navigation is inherently supported.
- At each viewpoint/configuration of the environment ξ, the amount of space that is visible is computed as $Visible(M, \xi)$



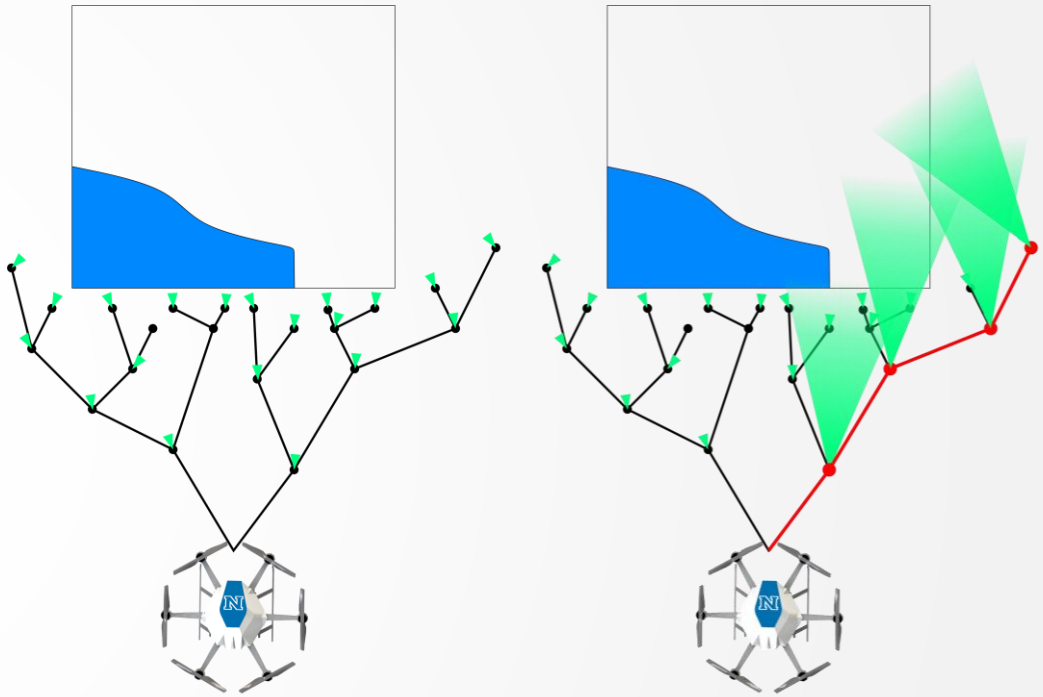
The Receding Horizon Next-Best-View Exploration Planner relies on the real-time update of the 3D map of the environment.

RH-NBVP Approach

- **Tree-based exploration:** At every iteration, RH-NBVP spans a random tree of finite depth. Each vertex of the tree is annotated regarding the collected Information Gain – a metric of how much new space is going to be explored.

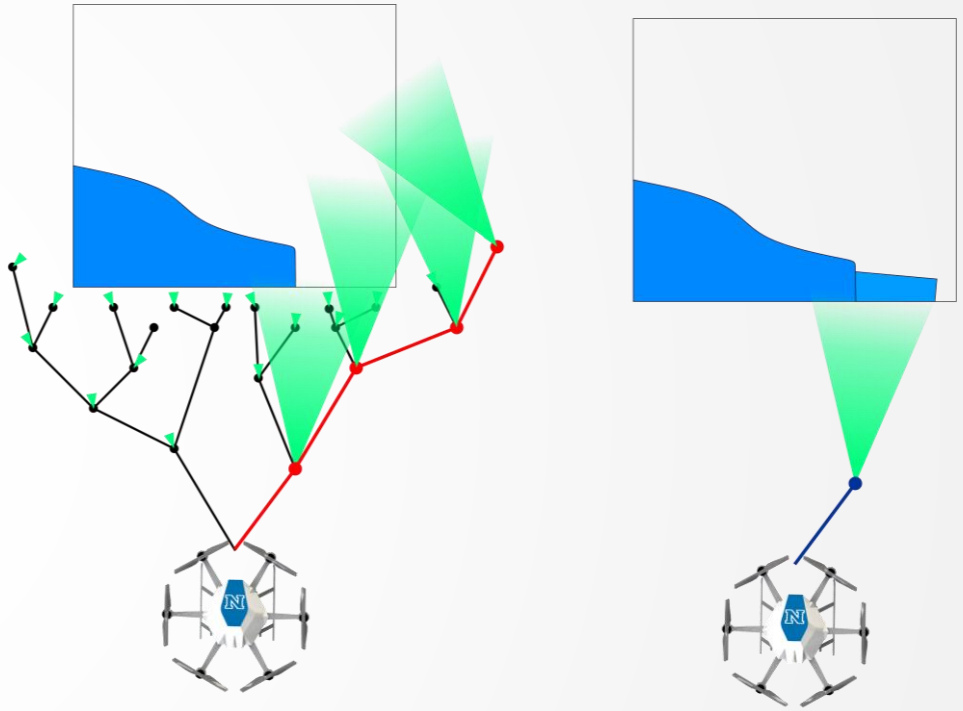
$$\mathbf{Gain}(n_k) = \mathbf{Gain}(n_{k-1}) + \mathbf{Visible}(\mathcal{M}, \xi_k) e^{-\lambda c(\sigma_{k-1}^k)}$$

- Within the sampled tree, evaluation regarding the path that overall leads to the highest information gain is conducted. This corresponds to the **best path** for the given iteration. It is a sequence of next-best-views as sampled based on the vertices of the spanned random tree.



RH-NBVP Approach

- **Receding Horizon:** For the extracted best path of viewpoints, only the first viewpoint is actually executed.
- The system moves to the first viewpoint of the path of best viewpoints.
- Subsequently, the whole process is repeated within the next iteration. This gives rise to a receding horizon operation.

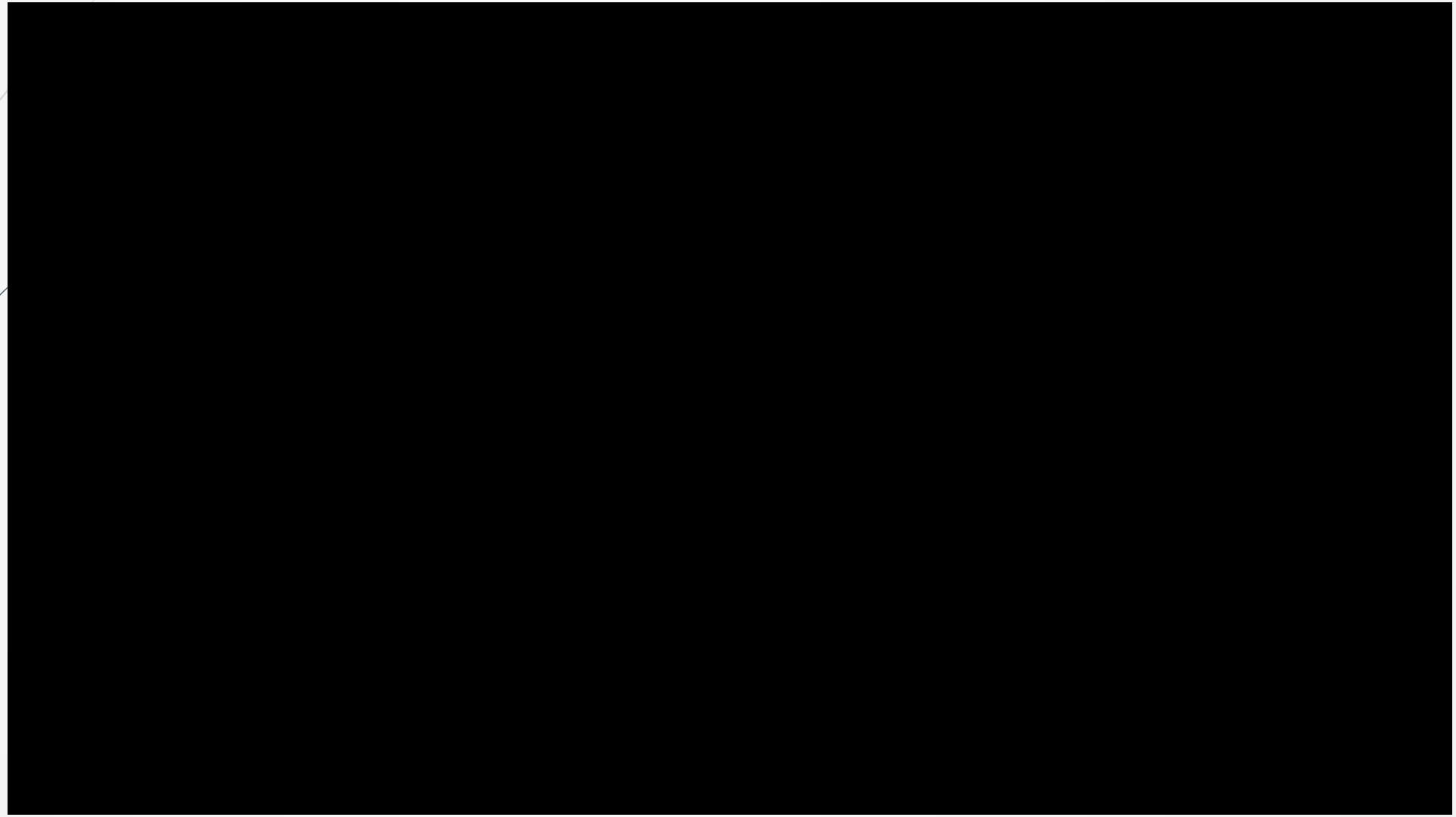


RH-NBVP Algorithm

NBVP Iterative Step

- $\xi_0 \leftarrow$current vehicle configuration
- Initialize $\boldsymbol{T}$ 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
- $N_T \leftarrow$Number of nodes in $\boldsymbol{T}$
- **while** $N_T < N_{max}$ or $g_{best} == 0$ **do**
  - Incrementally build T by adding $n_{new}(\xi_{new})$
  - $N_T \leftarrow N_T + 1$
  - **if** $Gain(n_{new}) > g_{best}$ **then**
    - $n_{best} \leftarrow n_{new}$
    - $g_{best} \leftarrow Gain(n_{new})$
  - **if** $N_T > N_{TOT}$ **then**
    - Terminate exploration
- $\sigma \leftarrow \boldsymbol{ExtractBestPathSegment}(n_{best})$
- Delete $\boldsymbol{T}$
- **return** σ

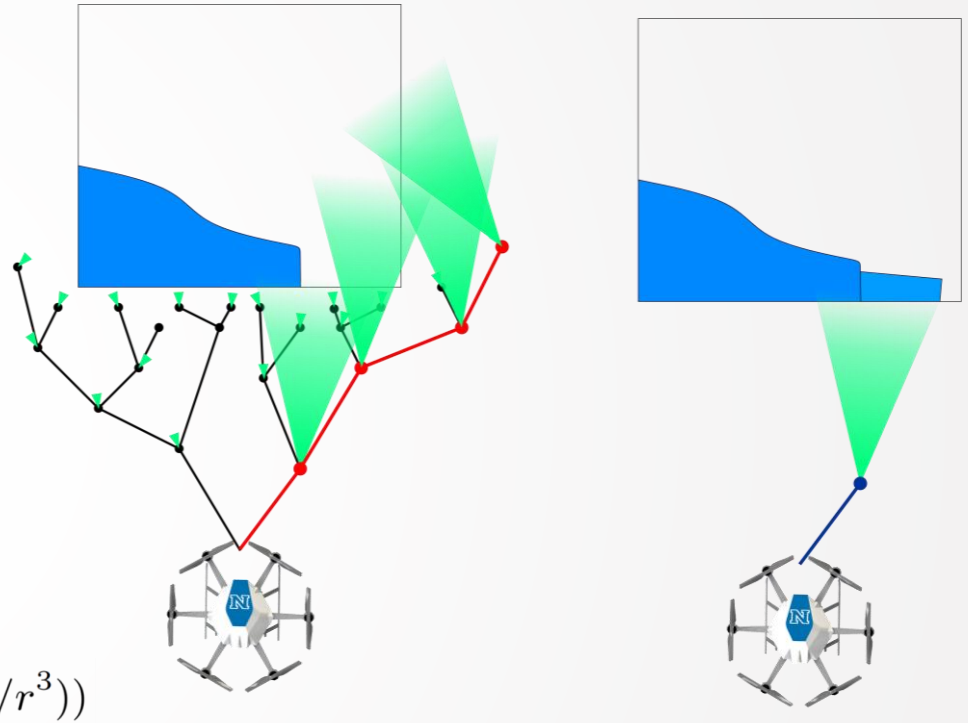
RH-NBVP in Action



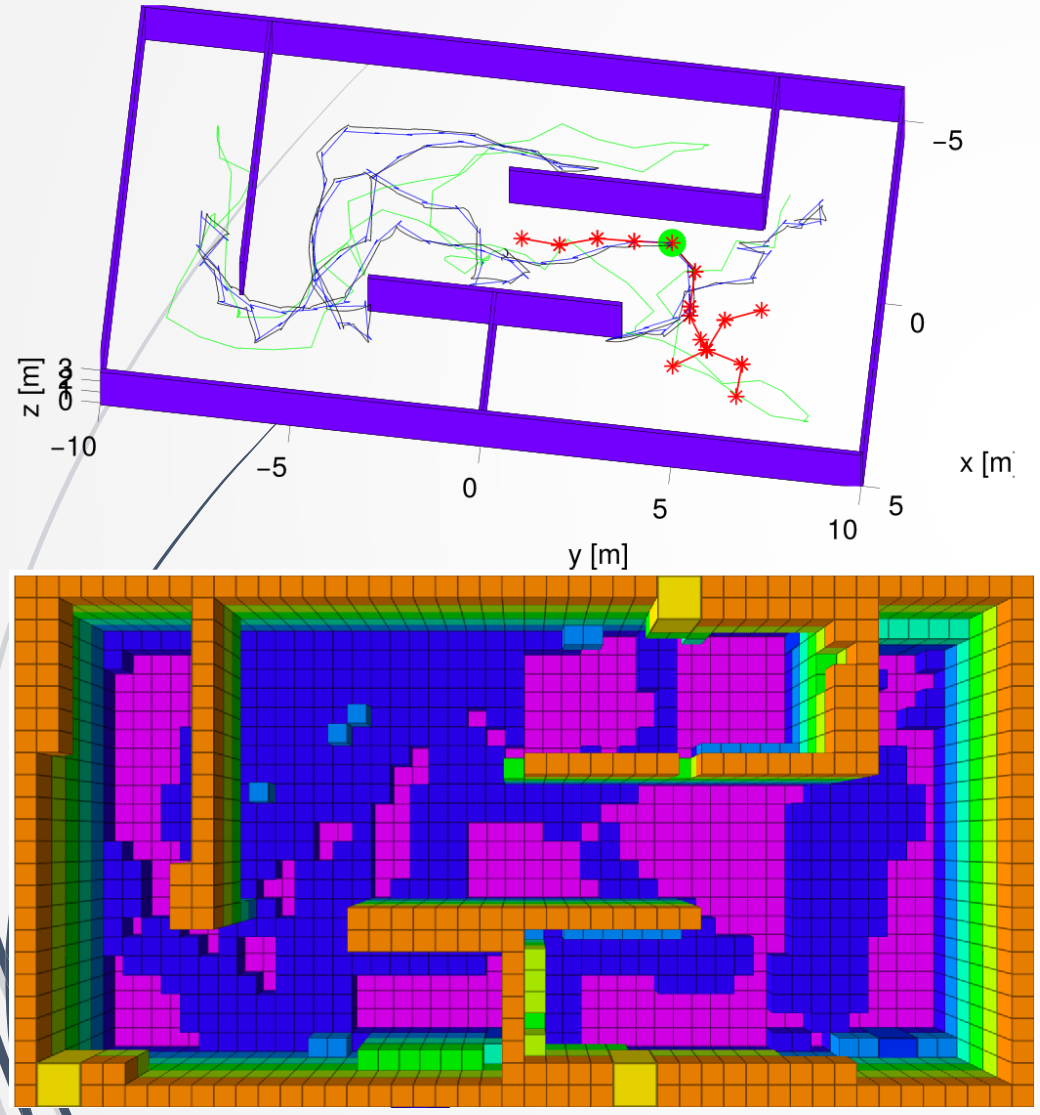
RH-NBVP Remarks

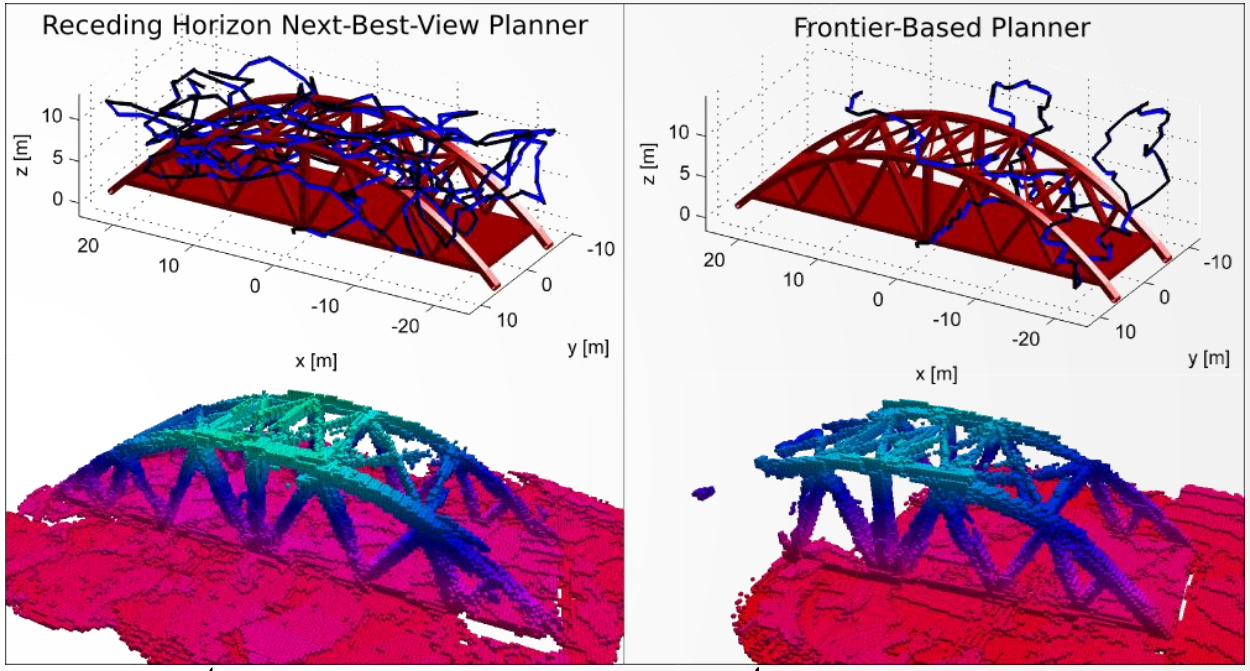
- **Inherently Collision-free:** As all paths of NBVP are selected along branches within RRT-based spanned trees, all paths are inherently collision-free.
- **Computational Cost:** NBVP has a thin structure and most of the computational cost is related with collision-checking functionalities. The formula that expresses the complexity of the algorithm takes the form:

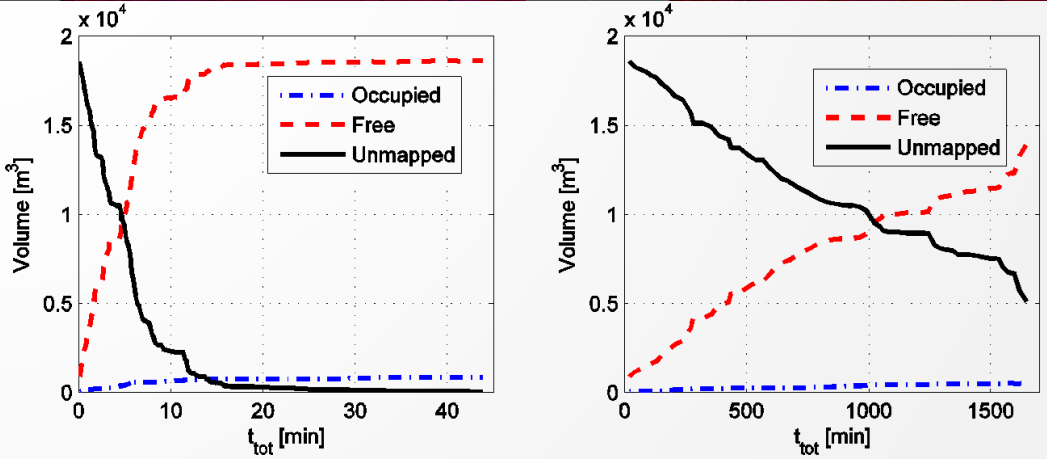
$$\mathcal{O}(N_{\mathbb{T}} \log(N_{\mathbb{T}}) + N_{\mathbb{T}}/r^3 \log(V/r^3) + N_{\mathbb{T}}(d_{\max}^{\text{planner}}/r)^4 \log(V/r^3))$$



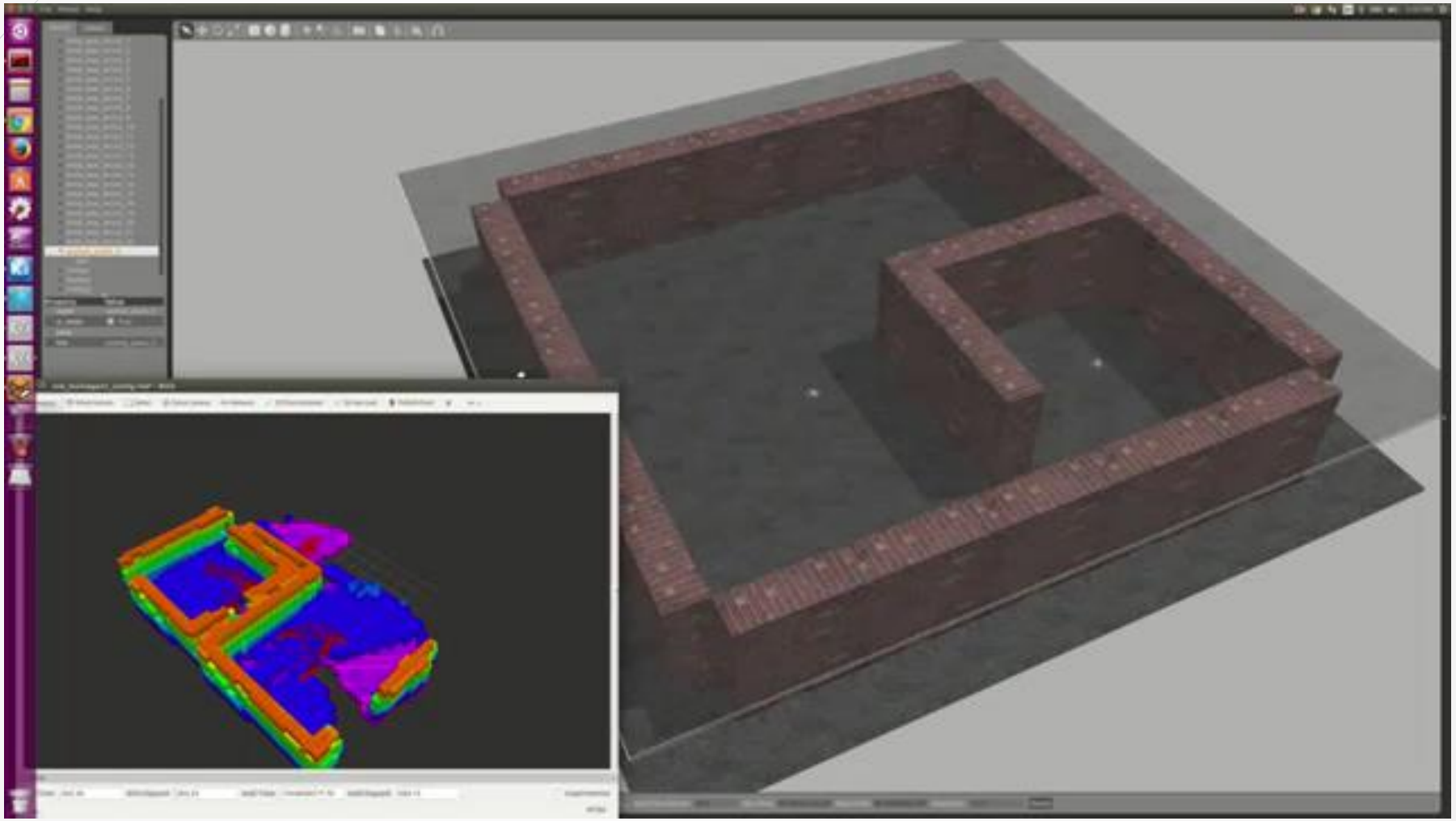
RH-NBVP Evaluation (Simulation)



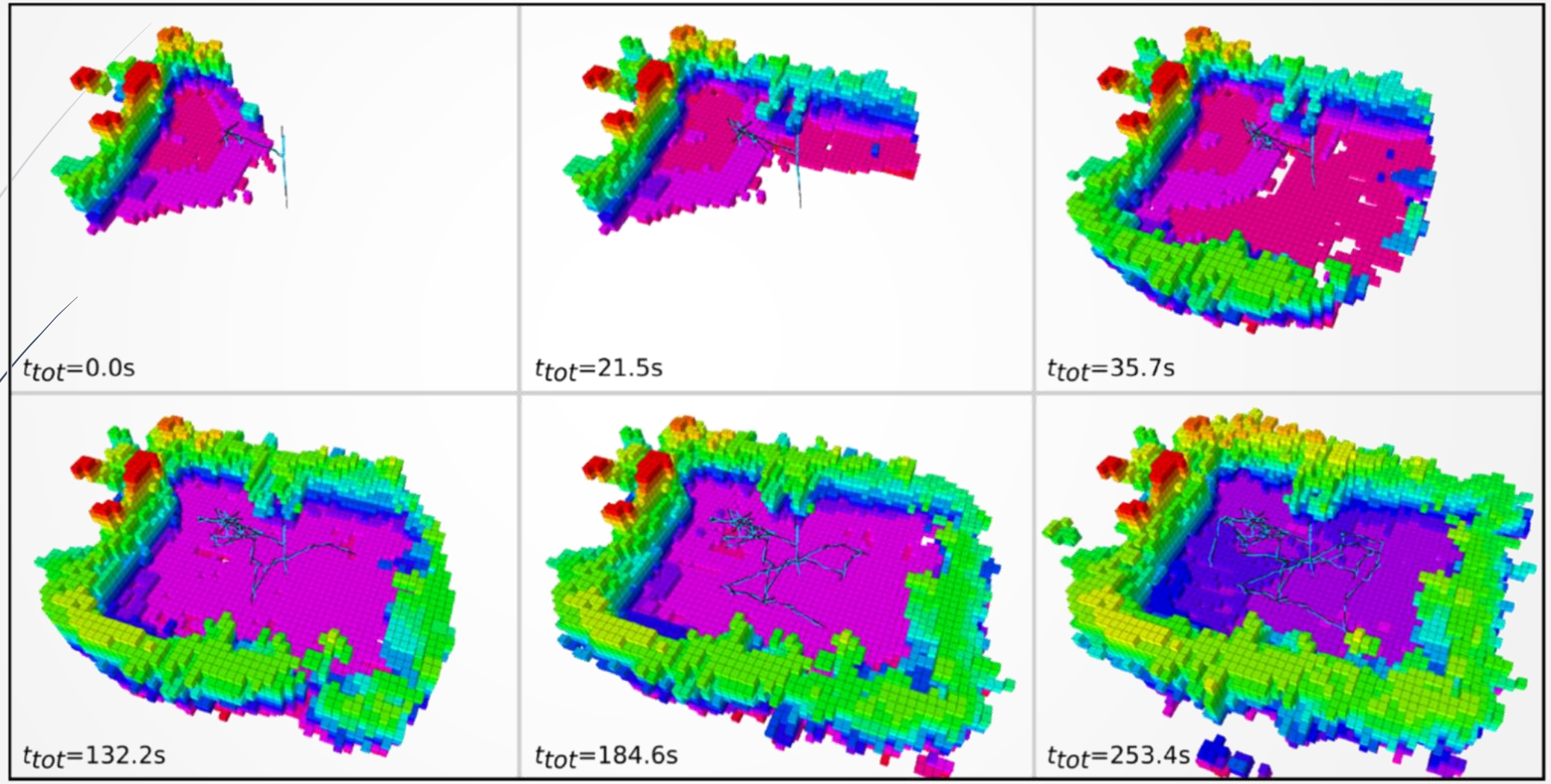




Multi-Agent RH-NBVP Simulation



RH-NBVP Evaluation (Experiment)



RH-NBVP further remarks

- Relies on the capability of the robot to localize itself and 3D reconstruct its environment.
- Very efficient geometric exploration. Not accounting for the statistics of the 3D reconstruction.
- Multi-agent extension further requires a collaboration strategy.

Be a developer

- **Open Source Code:**
  - Structural Inspection Planner:
    - https://github.com/ethz-asl/StructuralInspectionPlanner
  - Next-Best-View Planner:
    - https://github.com/ethz-asl/nbvplanner

- **Associated Datasets:**
  - Structural Inspection Planner:
    - https://github.com/ethz-asl/StructuralInspectionPlanner/wiki/Example-Results
  - Next-Best-View Planner:
    - https://github.com/ethz-asl/nbvplanner/wiki/Example-Results
  - Solar-powered UAV Sensing & Mapping:
    - http://projects.asl.ethz.ch/datasets/doku.php?id=fsr2015

Find out more

- http://www.kostasalexis.com/autonomous-navigation-and-exploration.html
- http://www.kostasalexis.com/holonomic-vehicle-bvs.html
- http://www.kostasalexis.com/dubins-airplane.html
- http://www.kostasalexis.com/collision-free-navigation.html
- http://www.kostasalexis.com/structural-inspection-path-planning.html

- http://ocw.mit.edu/courses/aeronautics-and-astronautics/16-410-principles-of-autonomy-and-decision-making-fall-2010/lecture-notes/
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- Kostas Alexis, Christos Papachristos, Roland Siegwart, Anthony Tzes, "Uniform Coverage Structural Inspection Path-Planning for Micro Aerial Vehicles", Multiconference on Systems and Control (MSC), 2015, Novotel Sydney Manly Pacific, Sydney Australia. 21-23 September, 2015
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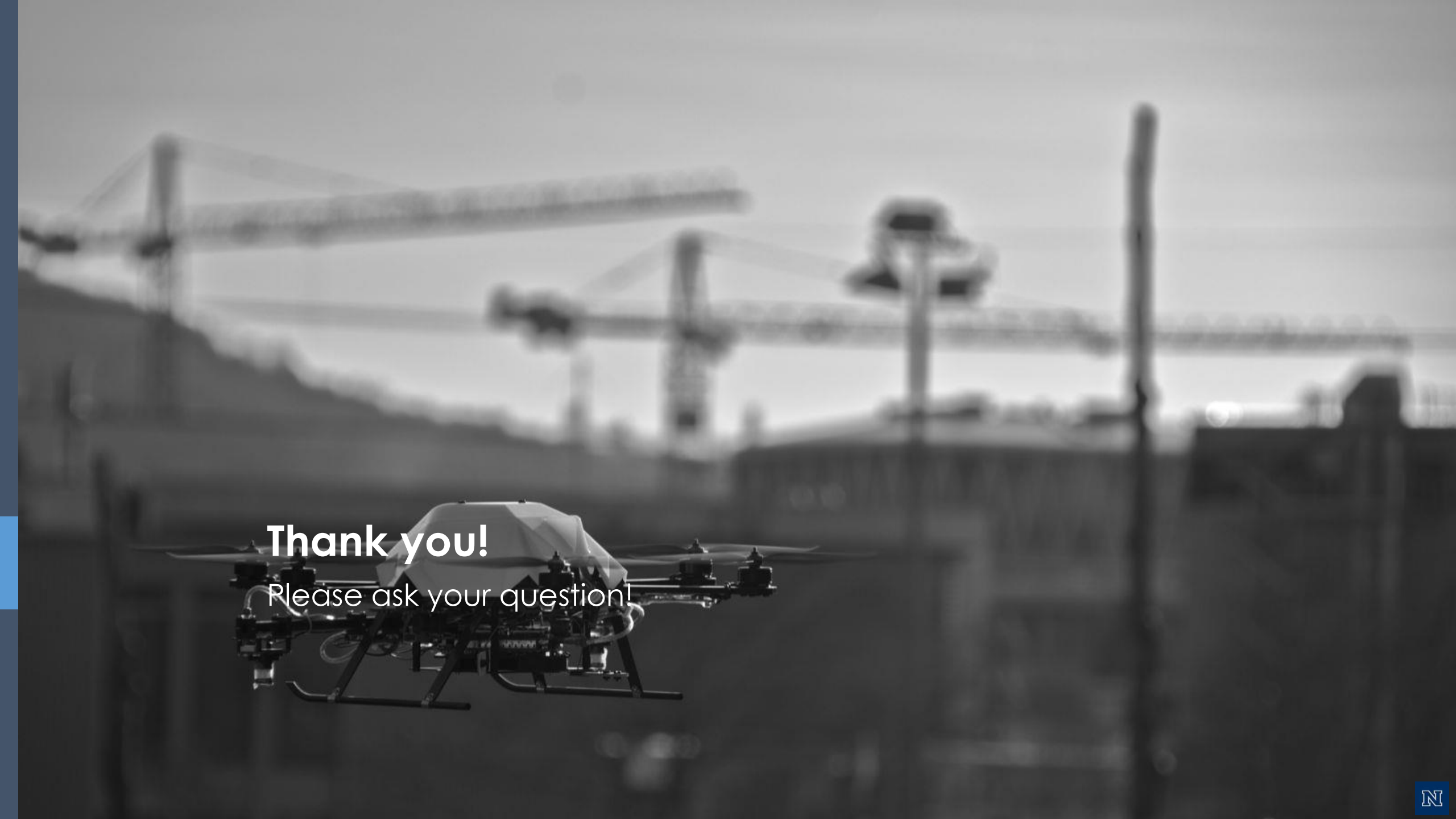
- A. Bircher, M. Kamel, K. Alexis, H. Oleynikova, R. Siegwart, "Receding Horizon "Next-Best-View" Planner for 3D Exploration", IEEE International Conference on Robotics and Automation 2016 (ICRA 2016), Stockholm, Sweden (Accepted - to be presented)



Thank you!

Please ask your question!