Autonomous Aerial Robots

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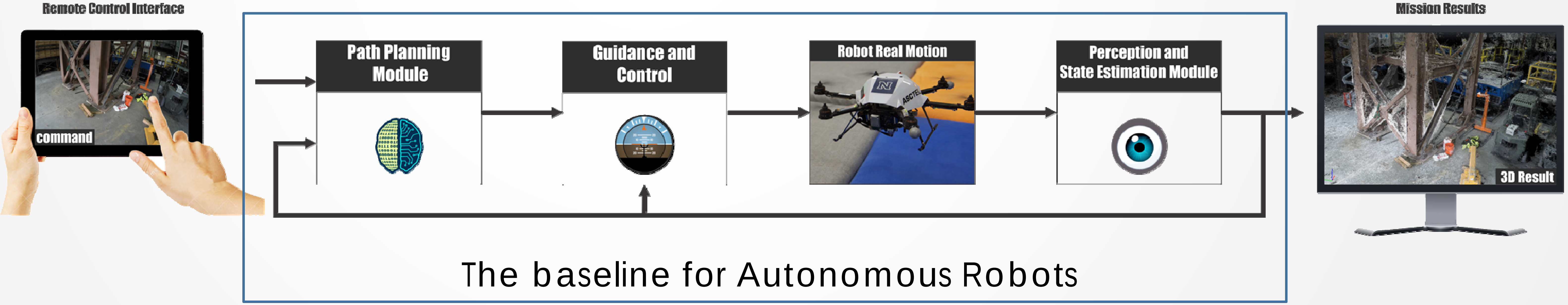
Constituents of Autonomy

- **Robotic Autonomy:**

  The ability to operate without the need for human action and reasoning and make own choices.

- Design sequence of moves that get it from *A* to *B*.
- Adhere by rules (e.g. avoid collisions).
- Optimize reponse and guarantee constraints.
- Exploit the best the robot has to offer.
- Robot Configuration has to allow operation in specific mission profile.
- Onboard equipment have to enable it too.
- Robust State Estimation required for ego-perception.
- Exteroceptive perception required to understand the environment.

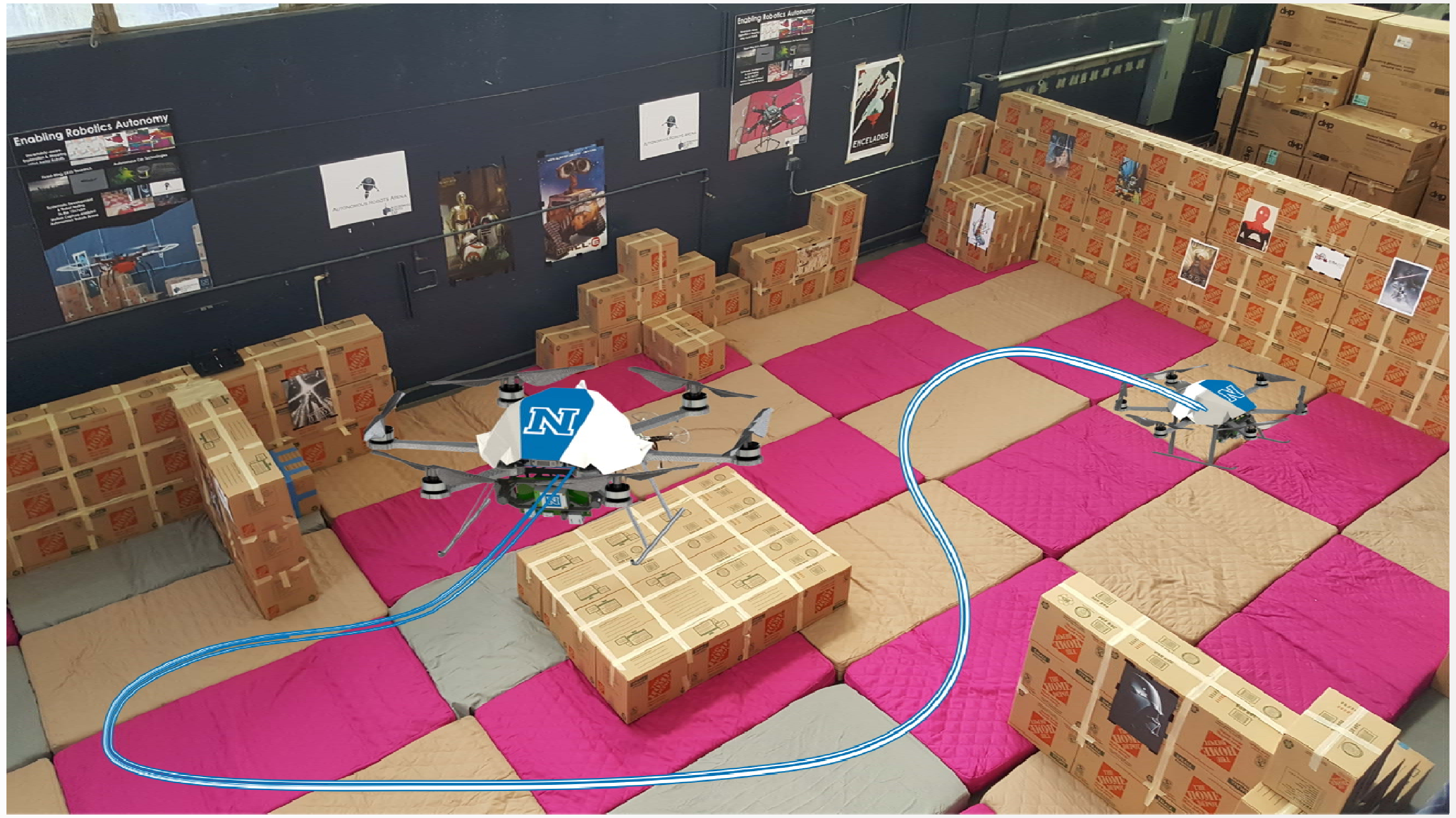


Constituents of Autonomy

- **Automatic Control:**

Autonomous Mobile Robot has to be in control of its own motion!

- No reliance on remote control / human teleoperation.
- The case for all robots, up to an extent.
- Depth & Complexity depend on specific platform, and specific application.

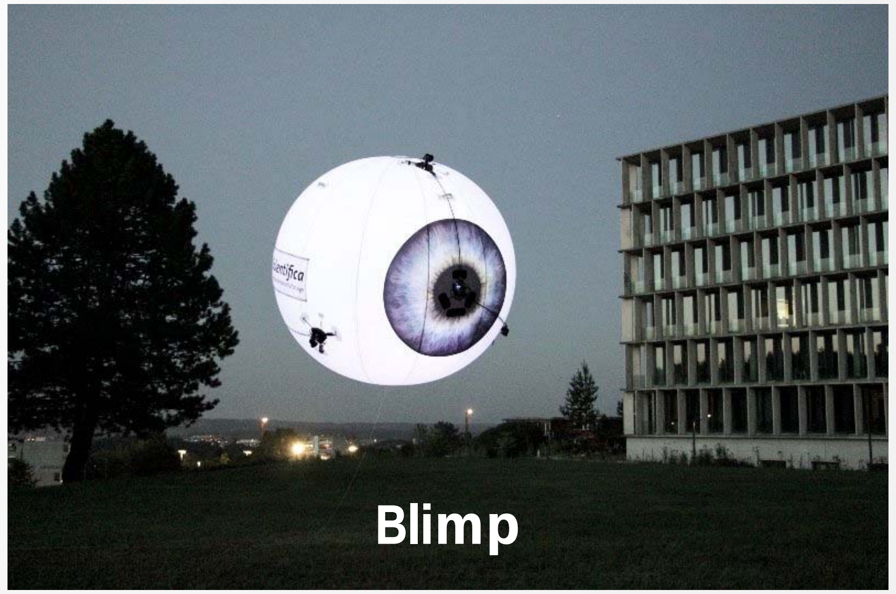


Constituents of Autonomy

- **Automatic Control:**

  The challenging case of Aerial Robots and their Control.

  - Need to stay airborne!
  - Particularly fast dynamics (for most aerial vehicles).



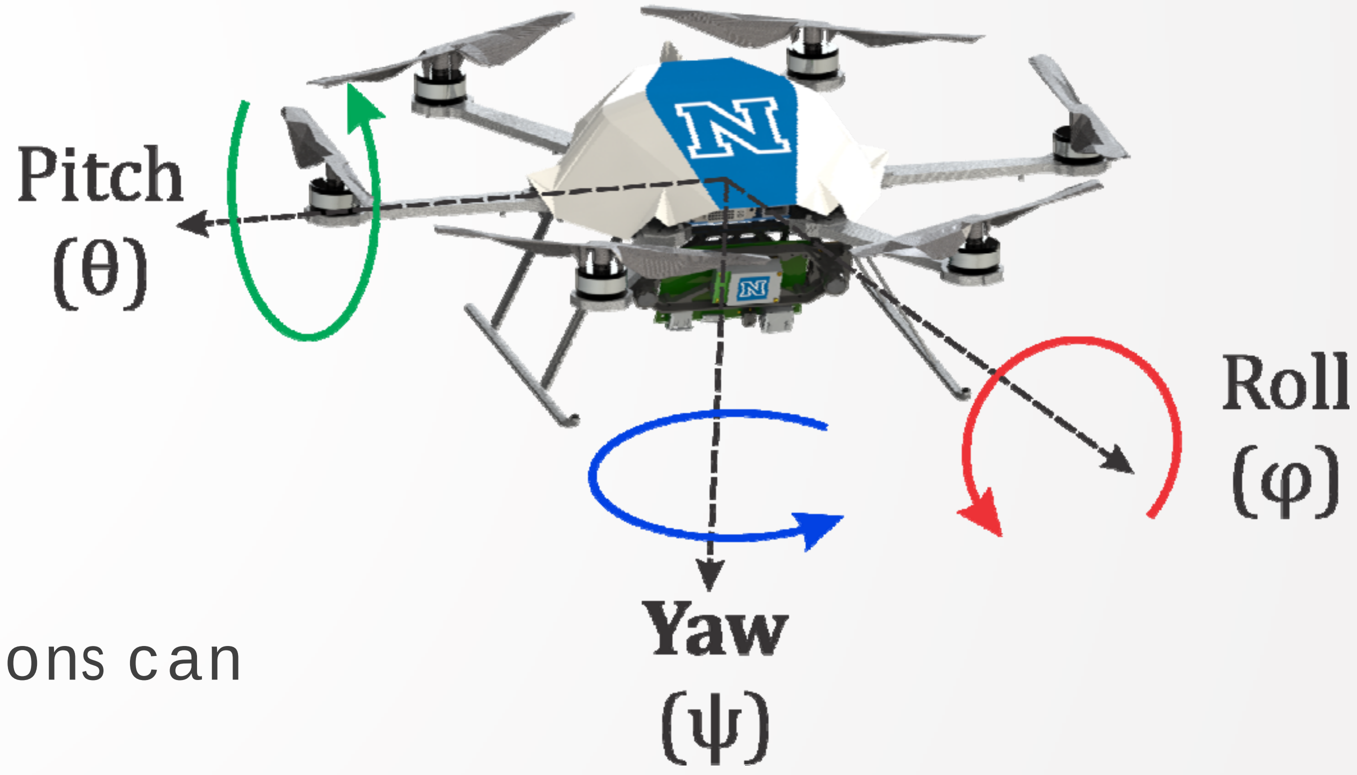
Constituents of Autonomy

- **Automatic Control:**

Multirotor Aerial Robot – 6-DoF Control Principles

Attitude Control:

- Simplest possible case treats the aerial robot as a "Rigid Body".
- Attitude refers to 3D orientation of the aerial vehicle.



The Aerial Vehicle is free-floating while airborne:

- Adjusting motor speeds in different combinations can generate Rotating Moments.
- The purpose of Attitude Control is to use this principle in order to "track" a specific 3D pose.

Constituents of Autonomy

- **Automatic Control:**

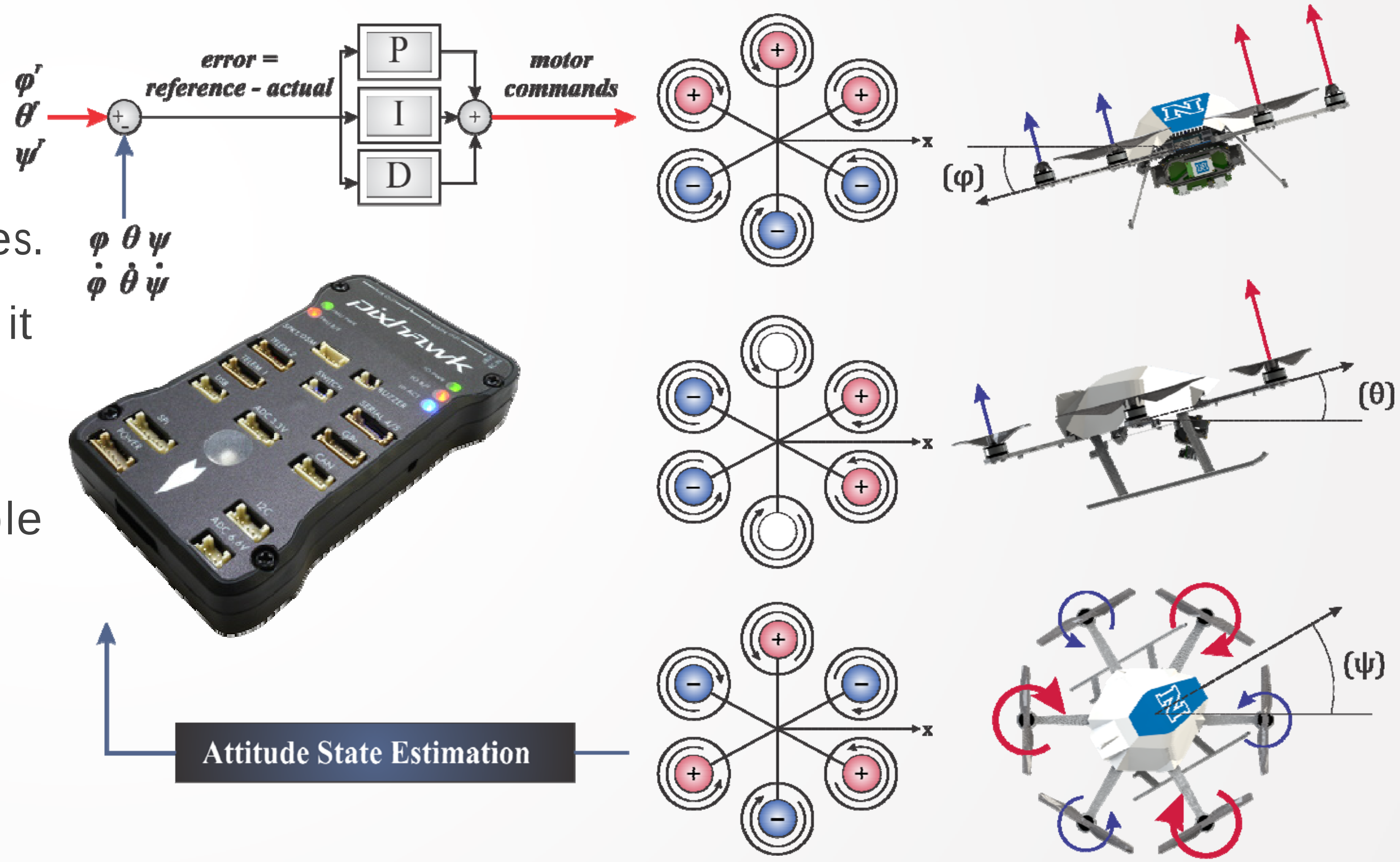
Multirotor Aerial Robot – 6-DoF Control Principles

Attitude Control:

- PID Control, calculates "distance" from desired values.
- Continuously tries to minimize it (reference tracking).

Handled by a "low-level" Autopilot. Commercially available systems offer complete solution:

- Attitude Control @ 200 Hz.
- Motor Driving interface.
- State Estimation.



Constituents of Autonomy

- **Automatic Control:**

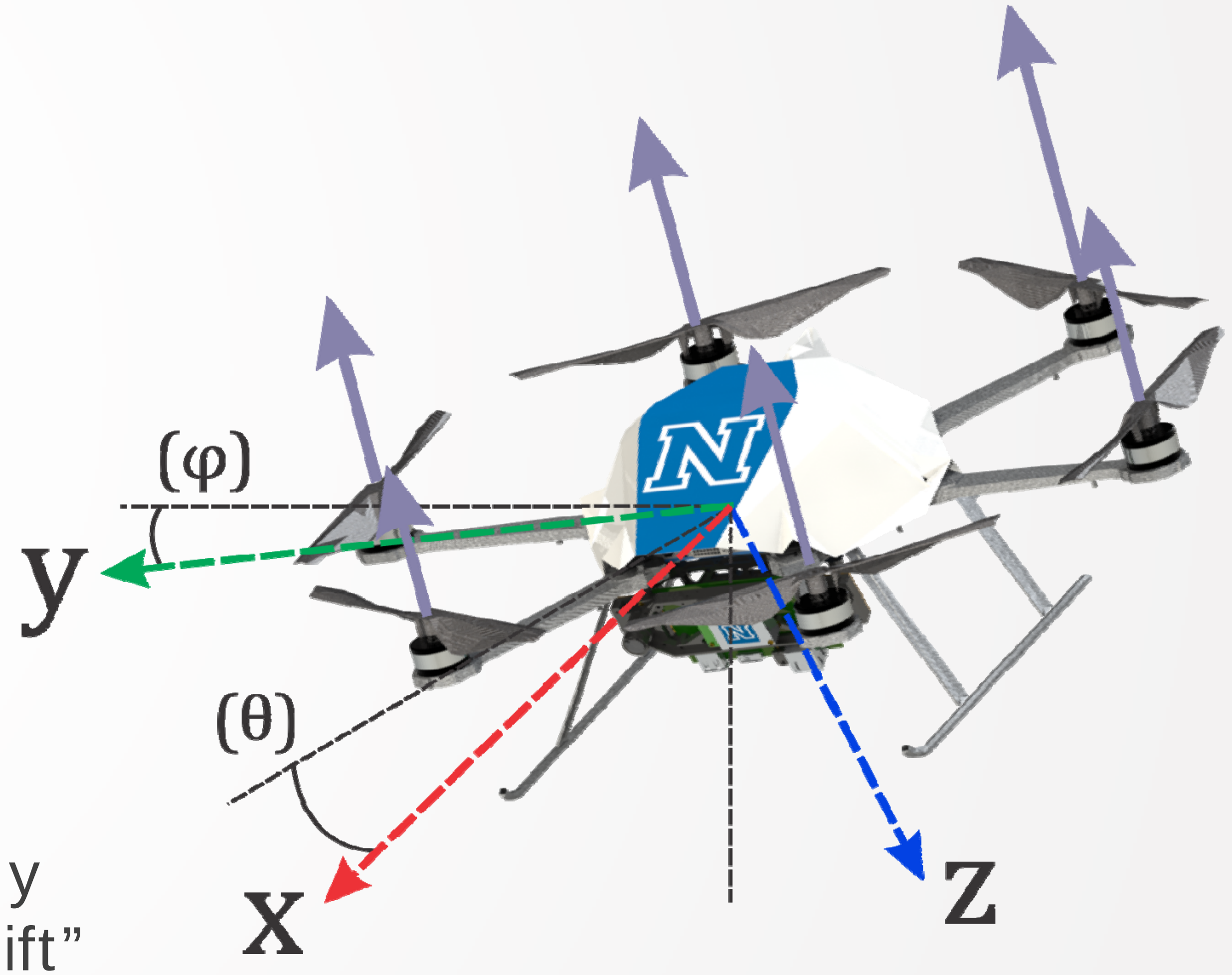
Multirotor Aerial Robot – 6-DoF Control Principles

Translation Control:

- Simplest possible case treats the aerial robot as a “Rigid Body”.
- Translation refers to 3D position of the aerial vehicle, and motion velocity (forward, sideways, and vertical).

The Aerial Vehicle is free-floating while airborne:

- Adjusting the sum of motor speeds “pulls” the body upwards. Adjusting the Attitude orients this “pull / lift” force forward / sideways / vertically.
- The purpose of Translation Control is to use this principle in order to move to and “track” a specific 3D position.



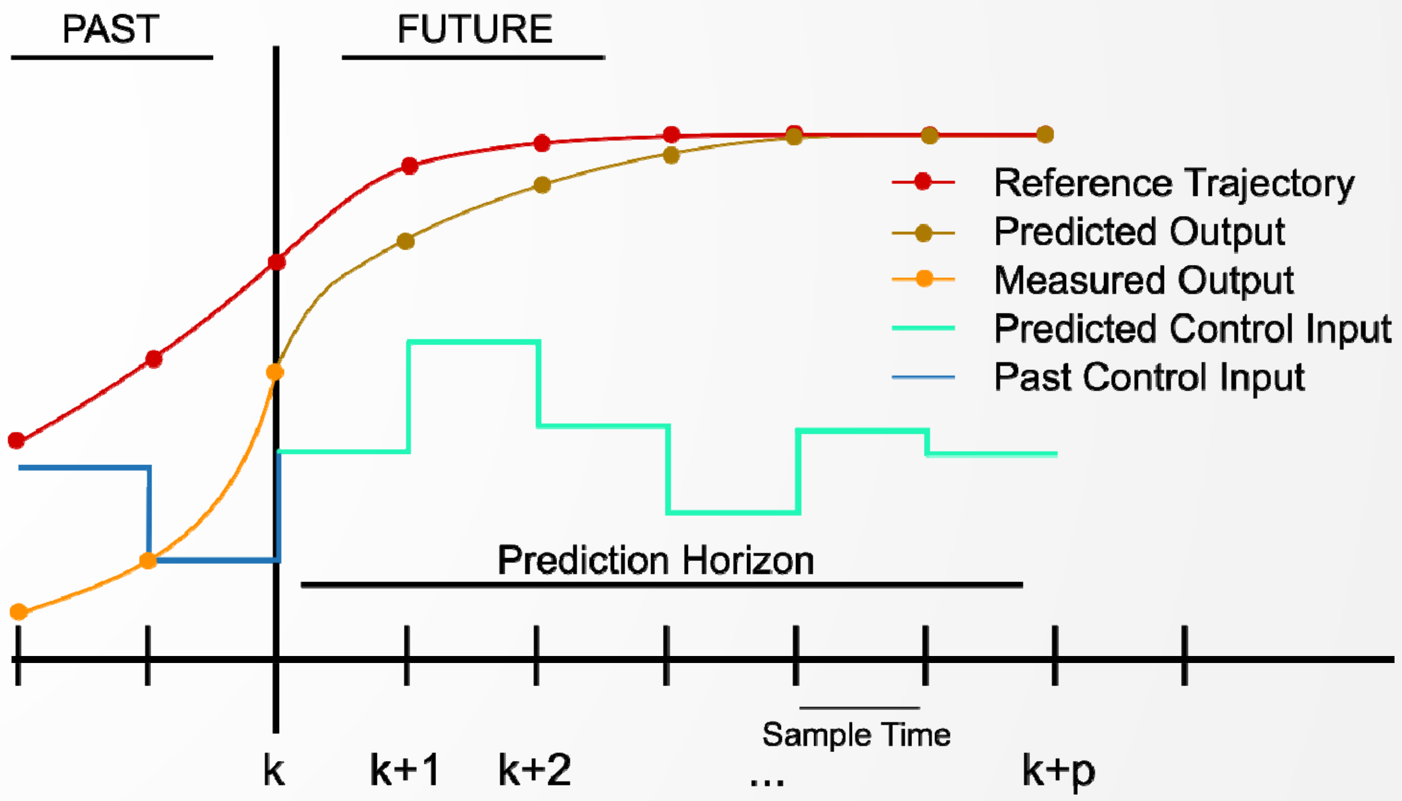
Constituents of Autonomy

Automatic Control:

Multirotor Aerial Robot – 6-DoF Control Principles

Translation Control:

- Model Predictive Control:
  Tries to perform tracking as well. But does so in control fashion that is:
- A) Optimal: "Knows" a dynamics model of the system model and "predicts" how a future sequence of control actions will affect it. Chooses the best.
- B) Receding-Horizon: Perform only the first action / move in the sequence. Then, it repeats the process based on the new State Estimates it gets.

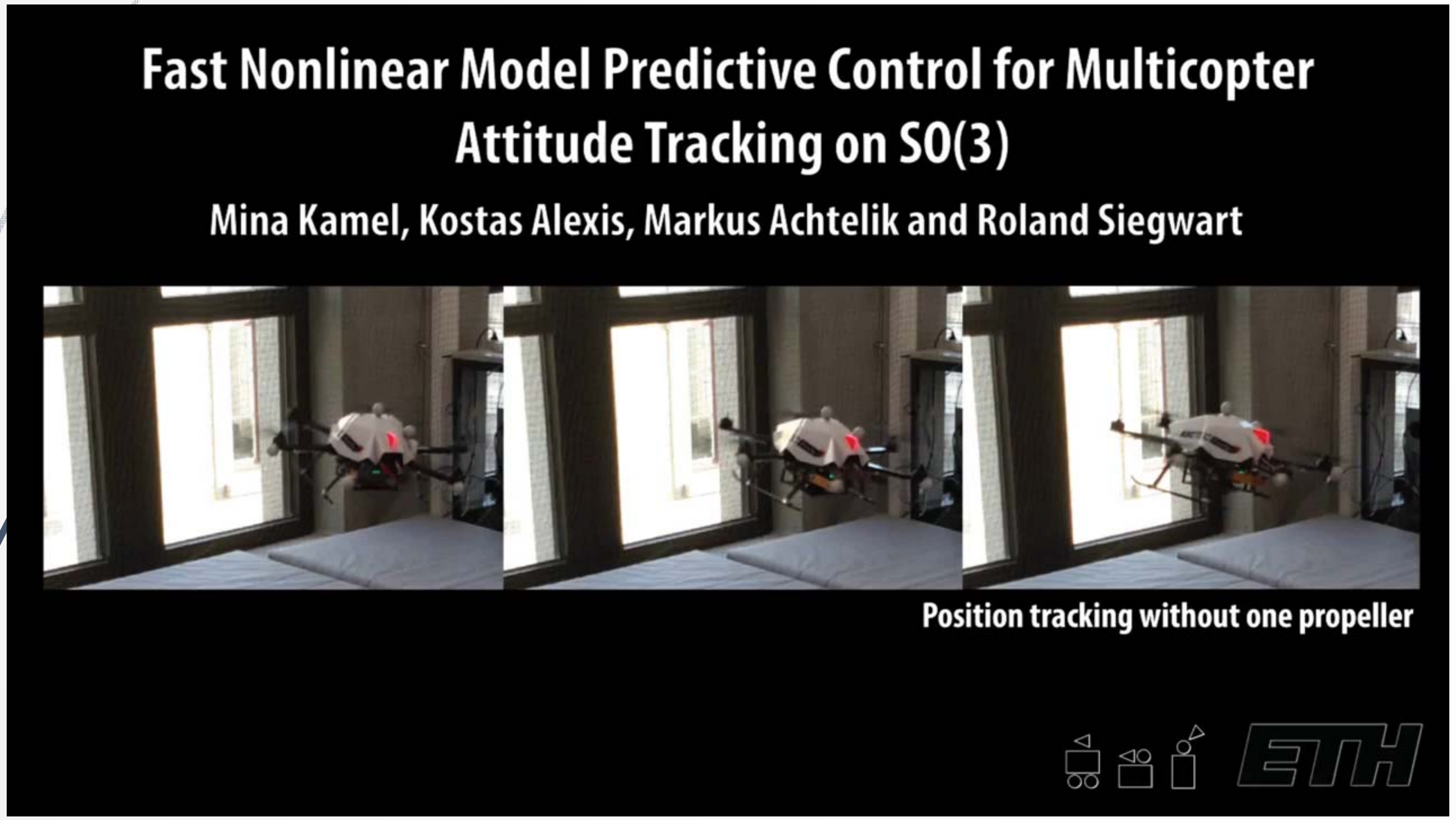


Like a human "Expert Pilot":
"Predicting" the effect of a sequence of future control moves based on the "expected" response.

Constituents of Autonomy

- **Automatic Control:**

  Model Predictive Control for Aerial Robots



Constituents of Autonomy

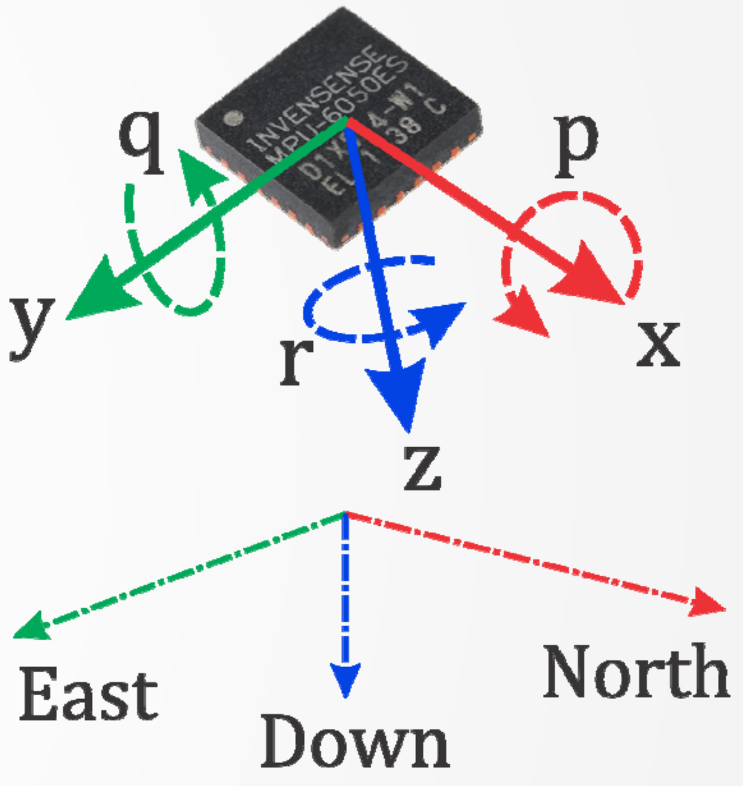
- **Perception & State Estimation:**

Attitude & Heading Reference System

Autonomy demands onboard sensing:

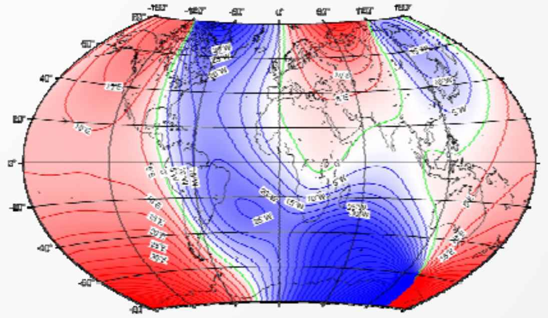
Inertial Sensors

- 3D Accelerometers & Gyroscopes.
- Accelerations and Rotational rates.
- Assumptions: a static gravitational field.



Additional Sensors

- Magnetometer, Barometer, Rangefinder, etc…
- Assumptions: a static magnetic field, barometric pressure field, etc.



Constituents of Autonomy

- **Perception & State Estimation:**

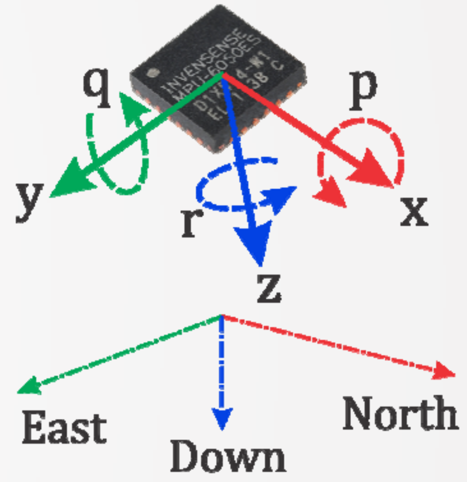
Attitude & Heading Reference System

Infer 3D Orientation w.r.t Earth's static reference frame:

- Directly by measuring acceleration components in all 3 body axes – But noisy!
- Indirectly by integrating rotational rates around body axes – But drifting!

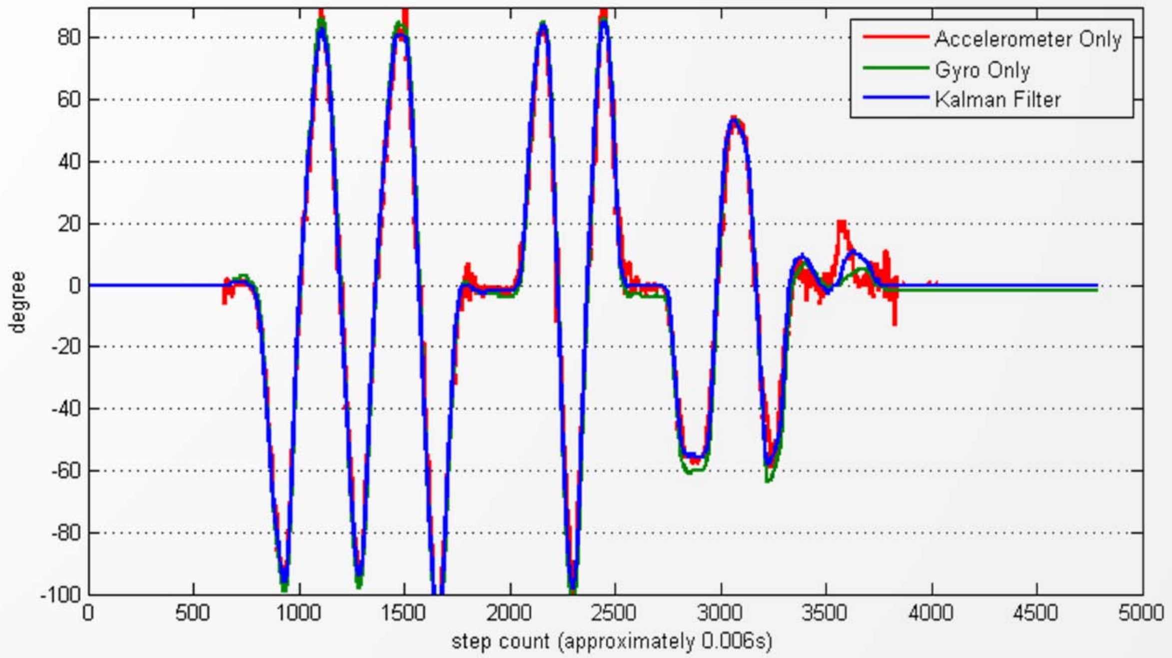
$$\boldsymbol{Sensor} \sim \begin{matrix} \tan^{-1} -y/z \\ \tan^{-1} x/z \end{matrix}$$

$$\boldsymbol{Model} \sim \int [p \quad q \quad r]^T dt$$



Onboard sensor fusion via Extended Kalman Filtering:

- Combining uncertain estimates from different processes: a) Sensor Model, b) System Model allows cross-correlation of uncertainties.
- If both are valid up to an extent, then the system's reality must lie "somewhere in-between".



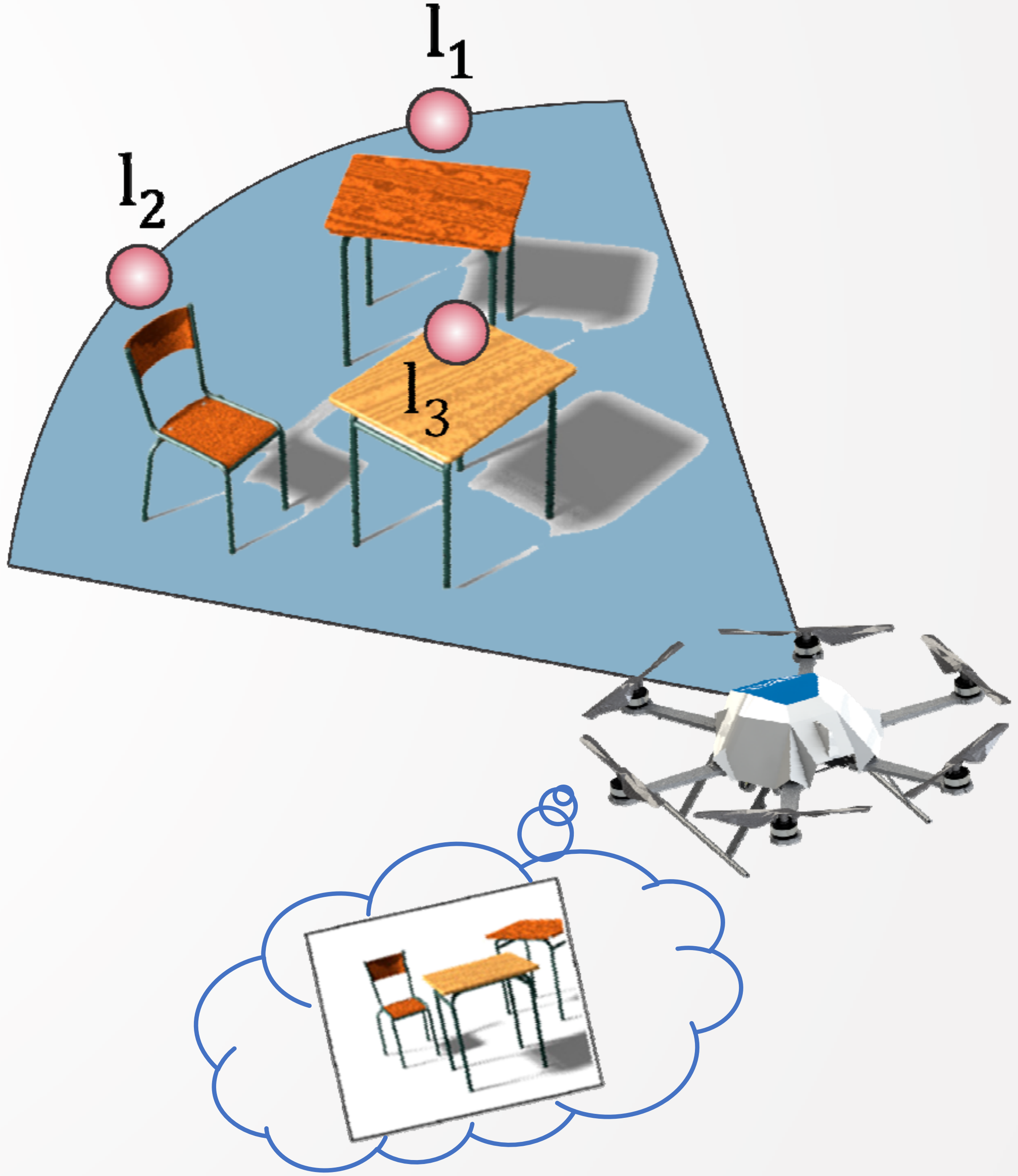
Constituents of Autonomy

- **Perception & State Estimation:**

Localization and Mapping

Autonomous 3D Position estimation:

- Localization against something (inside a Map). What if the Map landmark 3D positions are unknown?
- Mapping of an environment (calculation of landmarks' 3D positions) given robot's own pose. What if not provided?



Chicken & Egg problem of Inference:

- Where am I?
- Where are the things I see?

Constituents of Autonomy

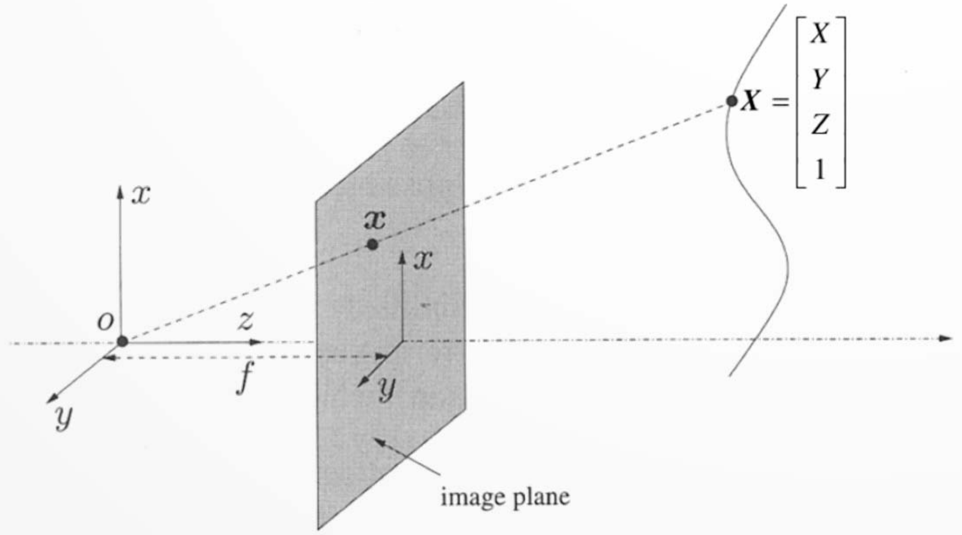
- **Perception & State Estimation:**

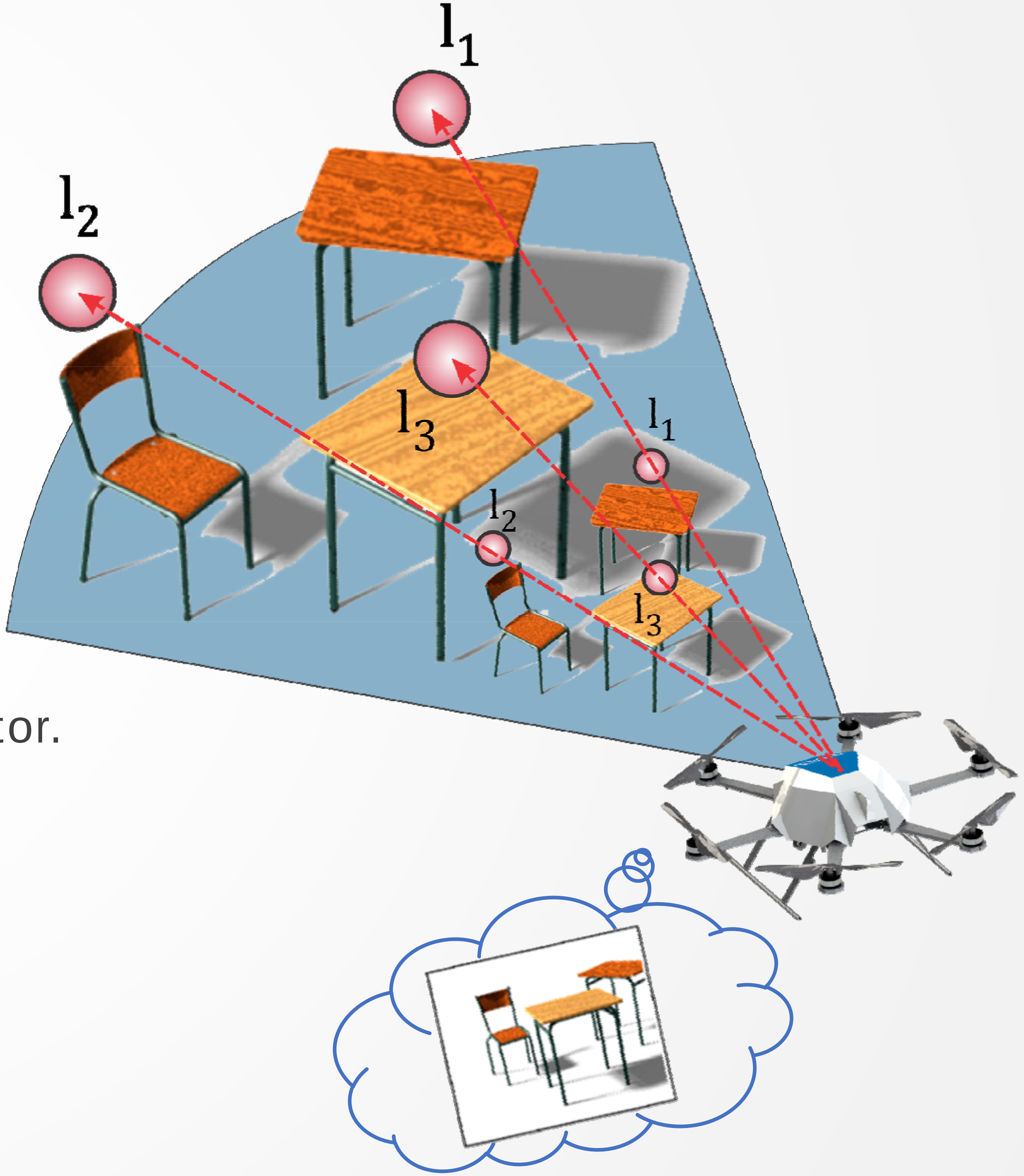
Localization and Mapping

Where are the things I see?

- A) 3D position of something in a picture (camera image pixel to 3D coordinates).

A camera is essentially a bearing sensor, everything else is recoverable up to a scale factor.





Constituents of Autonomy

- **Perception & State Estimation:**

Localization and Mapping

Where are the things I see?

- B) Understanding we see the same thing (frame-to-frame tracking)

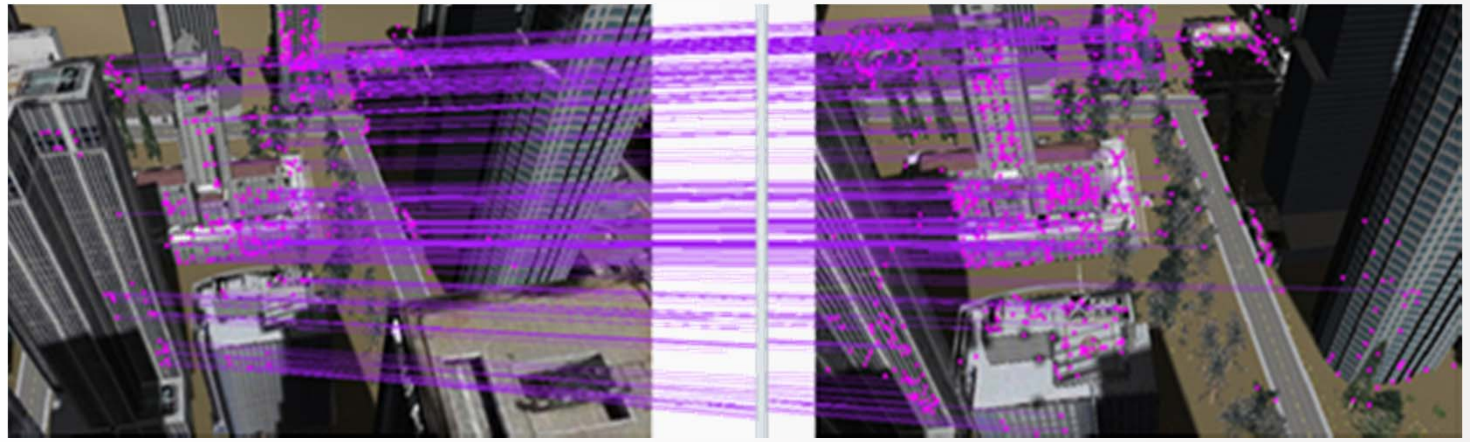
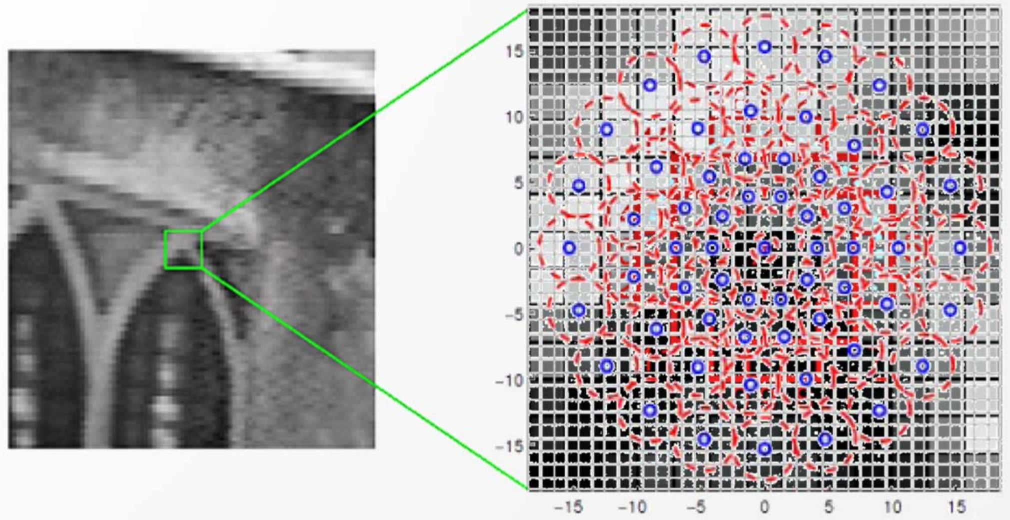


Image Features & Descriptors:

- Computing characteristic values a certain pixel's neighborhood allows selection of "strong" features for landmarks, and robustly finding them again in subsequent frames.



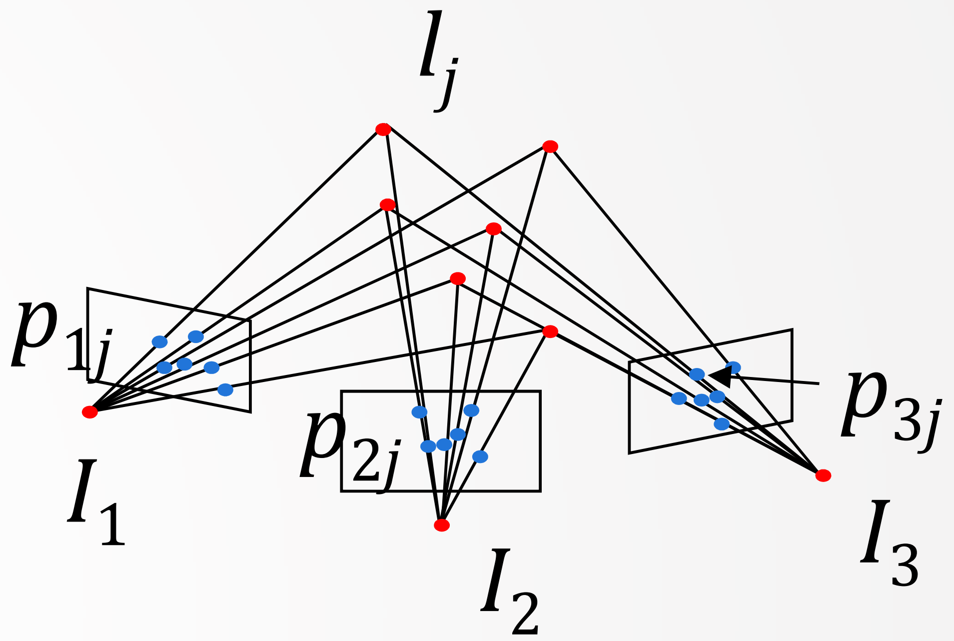
Constituents of Autonomy

- **Perception & State Estimation:**

Localization and Mapping

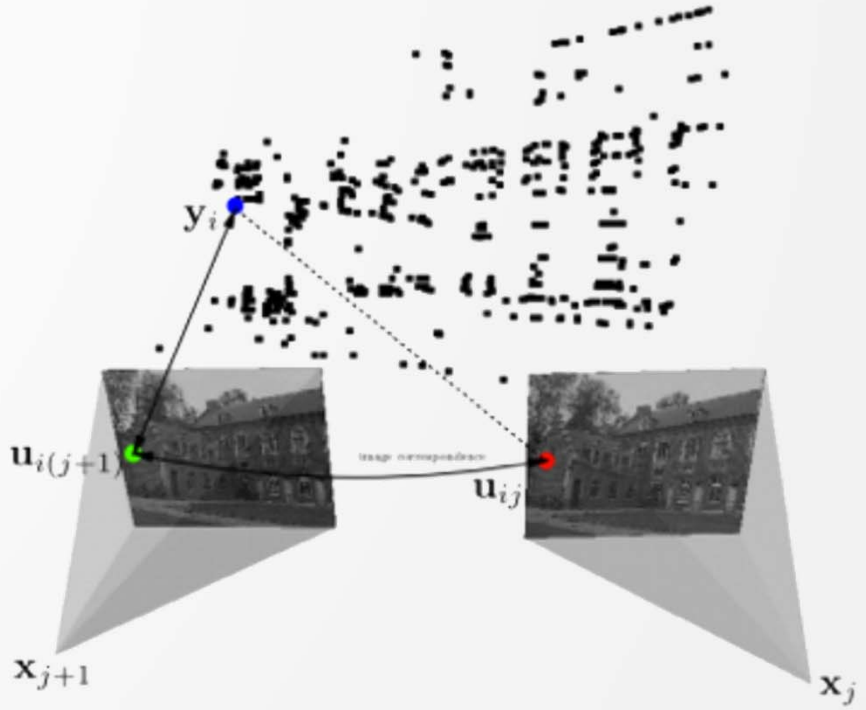
Where am I?

- How have I moved (from frame-to-frame)?
- Visual Odometry.



Use epipolar geometry to recover:

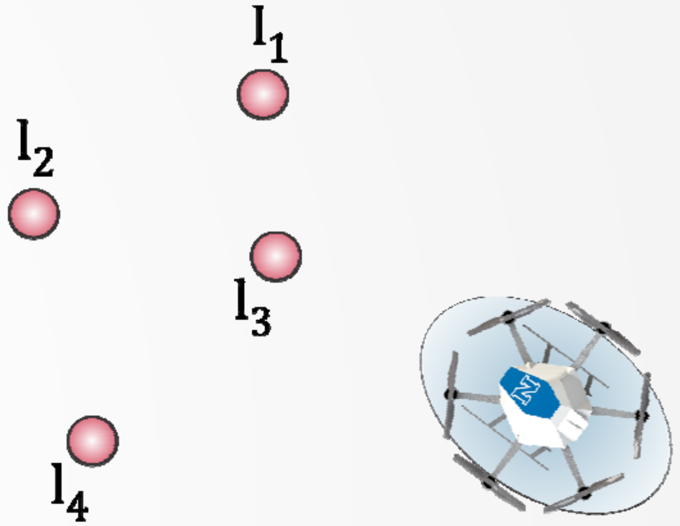
- Structure from Motion.
- Will end up with a solution from both problems, localization-&-mapping.



Constituents of Autonomy

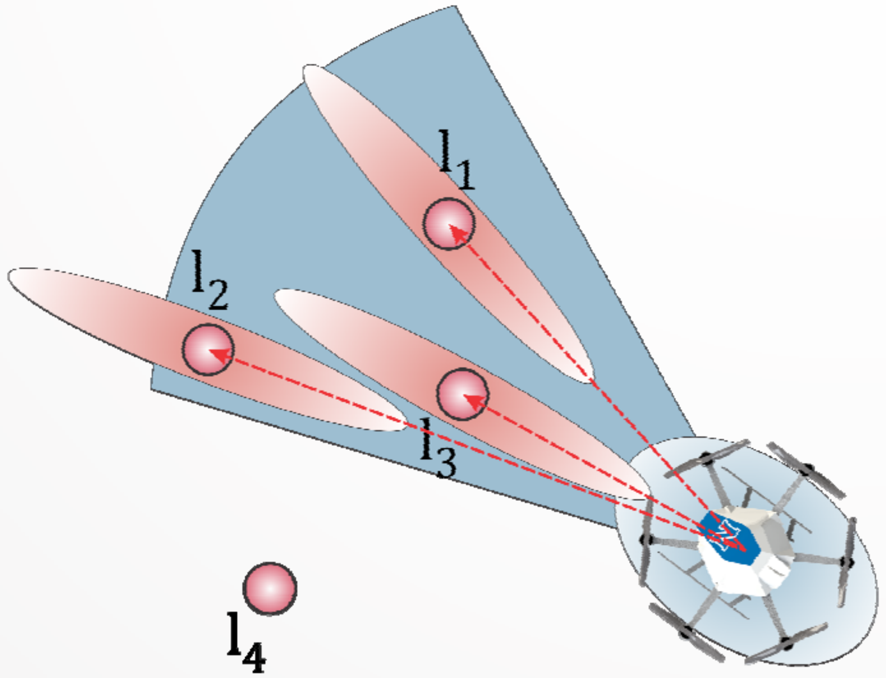
- **Perception & State Estimation:**

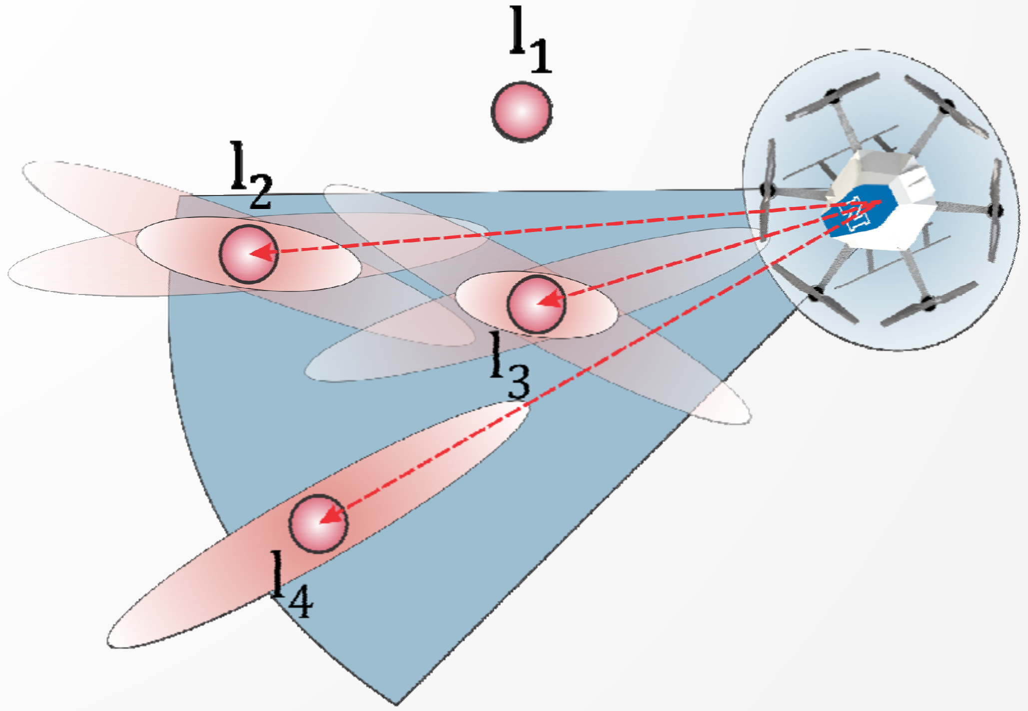
  Simultaneous Localization And Mapping (SLAM)



Frame-by-frame only will quickly drift!

- Correlation of robot pose uncertainty to measurement uncertainty (landmark 3D positions).
- Information Fusion of Processes that contain uncertainty.

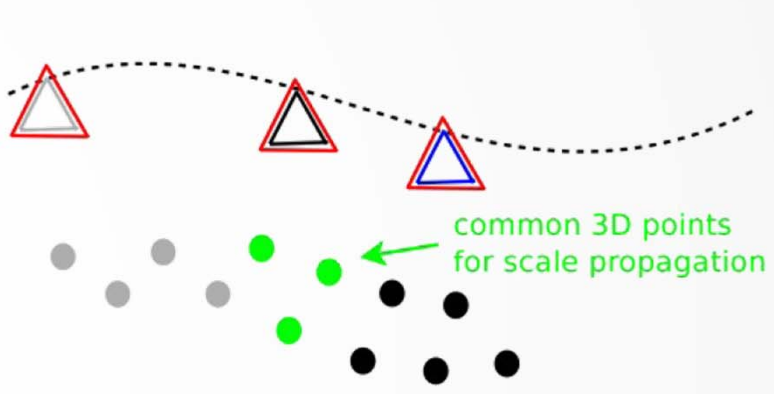


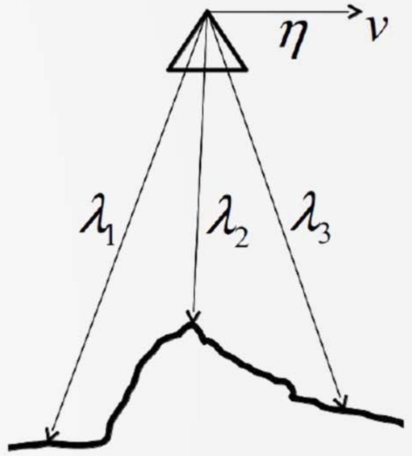


Constituents of Autonomy

- **Perception & State Estimation:**

Simultaneous Localization And Mapping (SLAM)



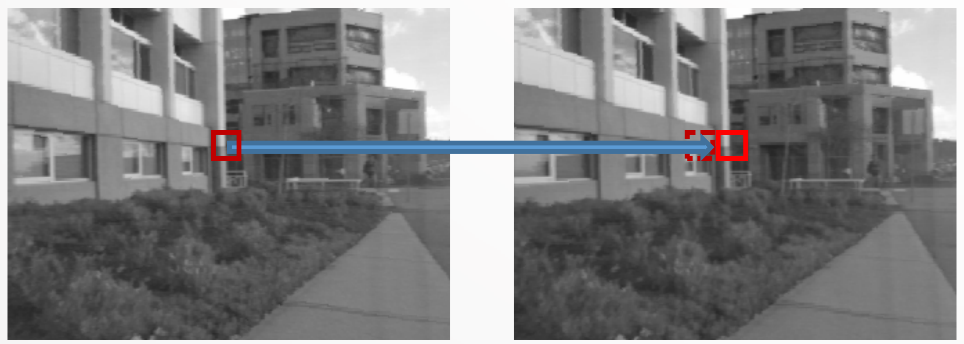


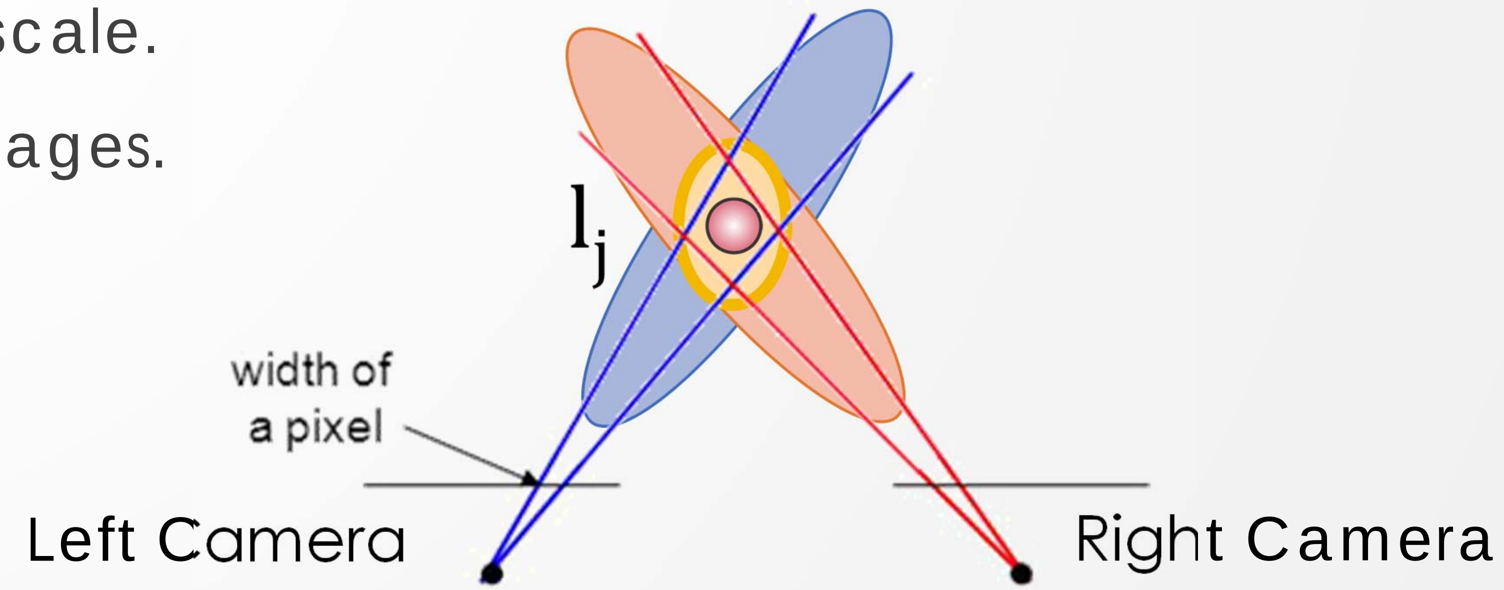
What about absolute scale?

- Scale can be estimated frame-to-frame (relative scale) and tracked.

1 solution: Stereo Visual Odometry

- Known baseline allows to directly estimate scale.
- Have to observe landmark on left & right images.





Constituents of Autonomy

- **Perception & State Estimation:**

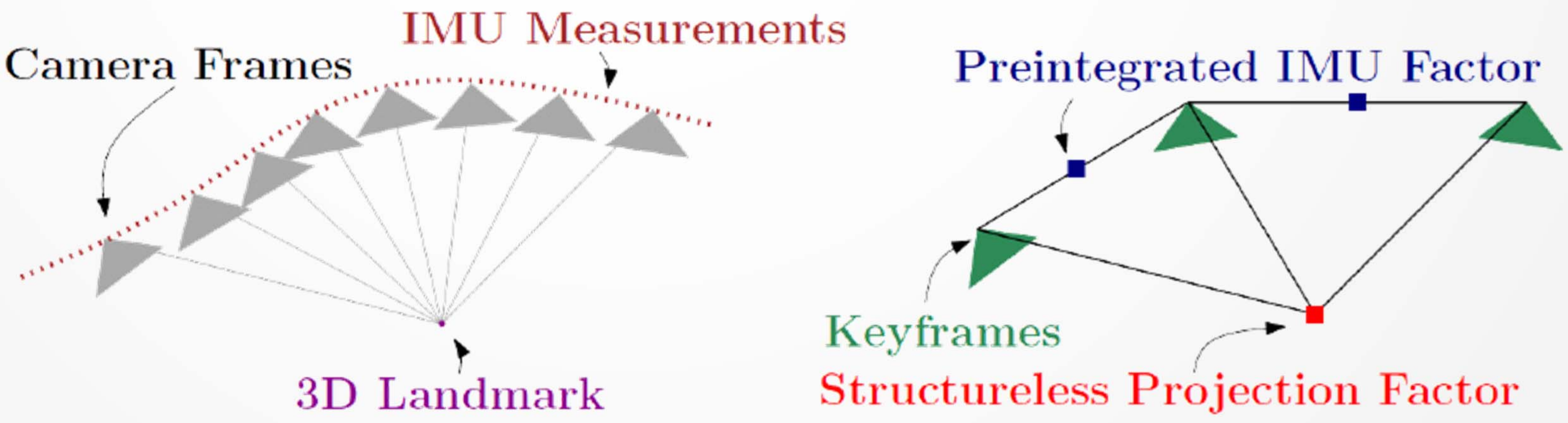
  Simultaneous Localization And Mapping (SLAM)

  Inertial Sensor Data have absolute scale too!

  - Visual-Inertial Localization.

  Velocity and scale become recoverable from 1 landmark and 3 subsequent observations.

  (also acceleration data are better than assuming frame-to-frame constant velocity)



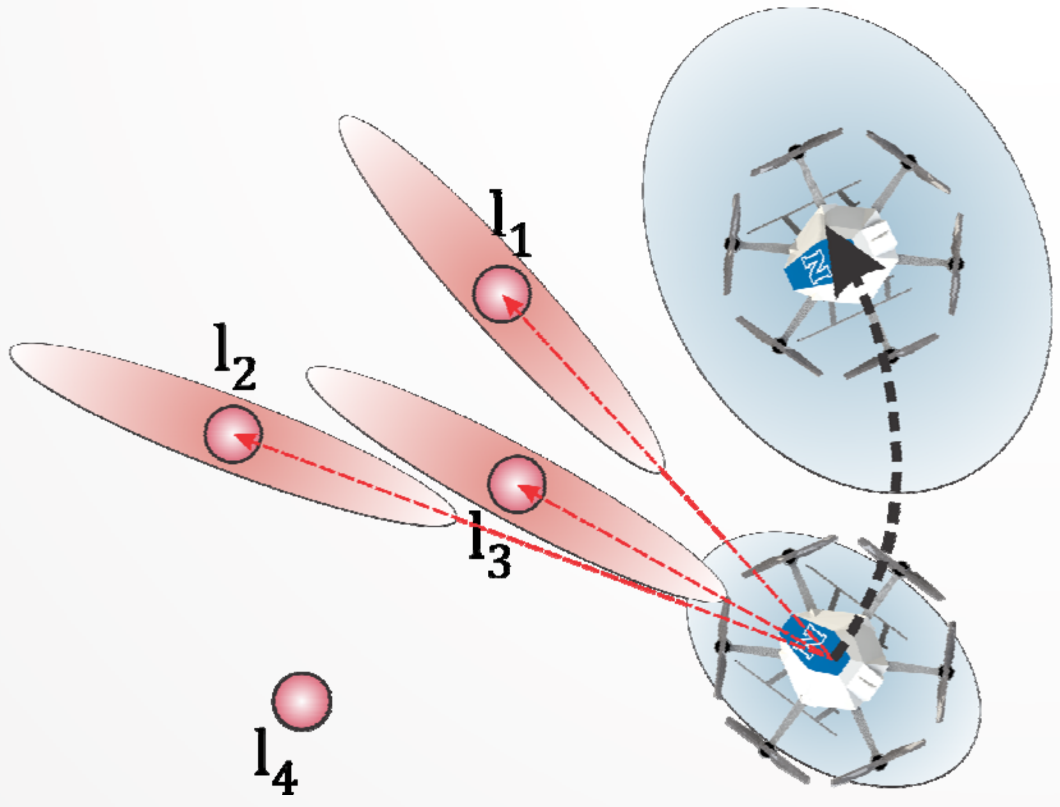
Constituents of Autonomy

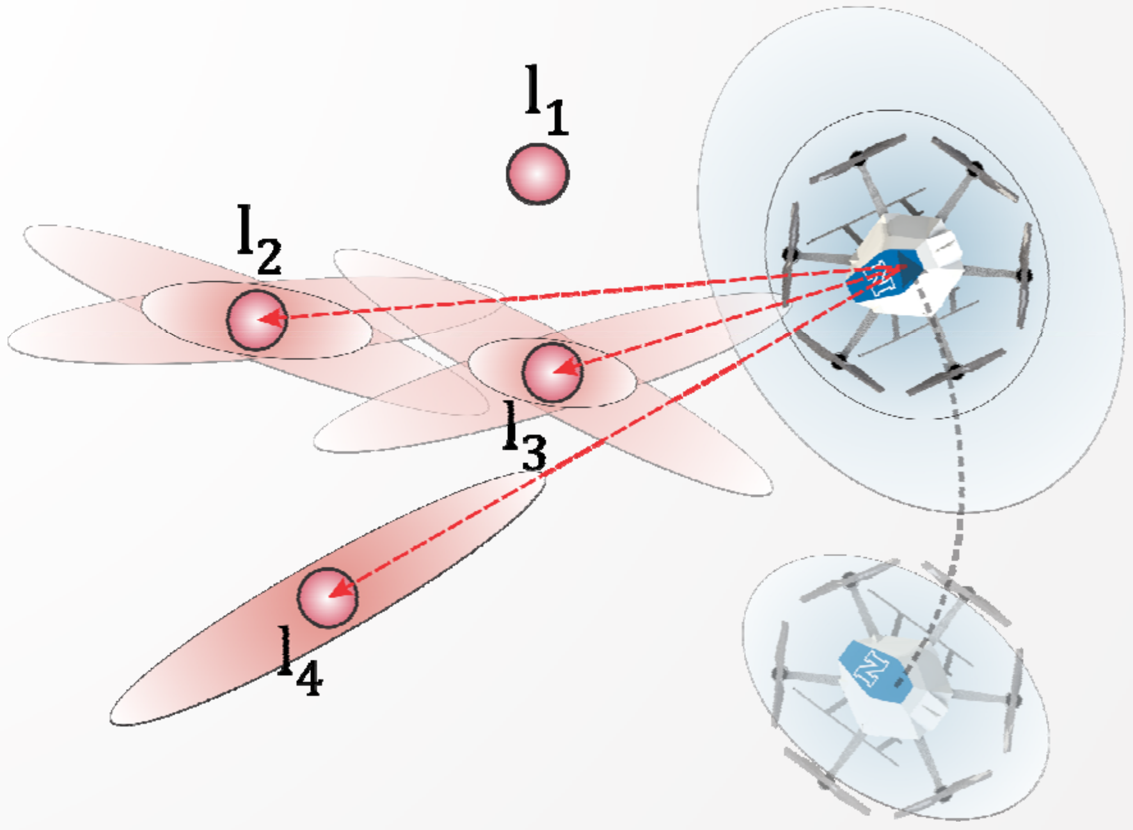
- **Perception & State Estimation:**

  Simultaneous Localization And Mapping (SLAM)

  Visual-Inertial Localization – Filter-based approach:

  - System Model: Propagation of Estimate & Uncertainty based on Rigid Body model and accelerometer & gyroscope data.
  - Measurement Model: Correction based on landmark-states observation (camera-based feature detection).

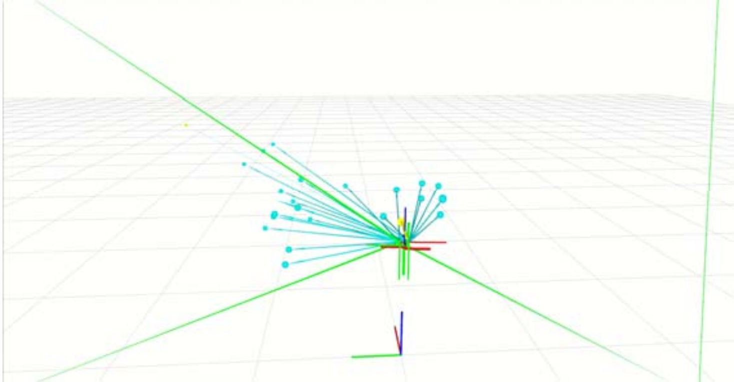




Constituents of Autonomy

- **Perception & State Estimation:**

Visual-Inertial Localization



Visual-Inertial Localization:

- Filter-based approach.
- Data are fused based on their statistics (noise is ok).
- But data timestamps have to be accurate (although data themselves not necessarily synchronized in their time-of-acquisition).

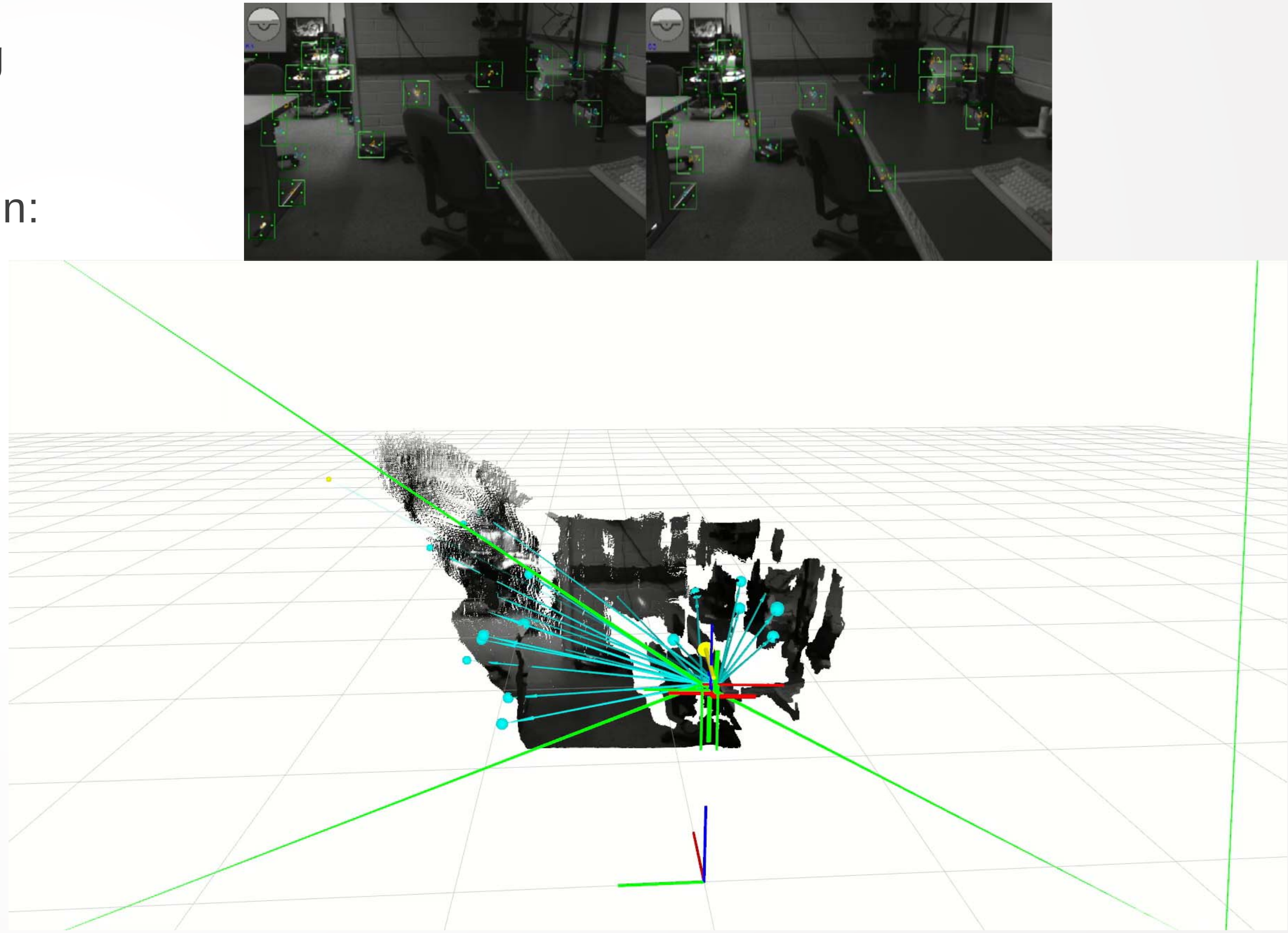
Constituents of Autonomy

- **Path-planning:**

  3D-Reconstruction and Mapping

  Stereo Visual - Inertial Localization:

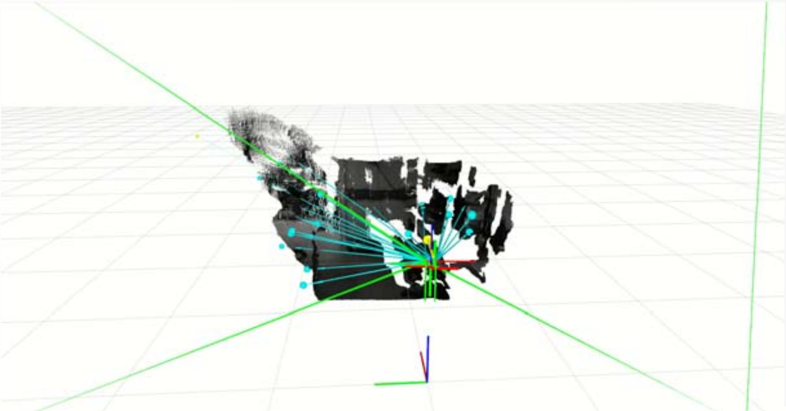
  - Reliable stereo camera model gives better landmark estimation statistics.
  - Robot 3D pose estimation is improved.
  - Stereo depth map 3D world projection becomes more consistent.



Constituents of Autonomy

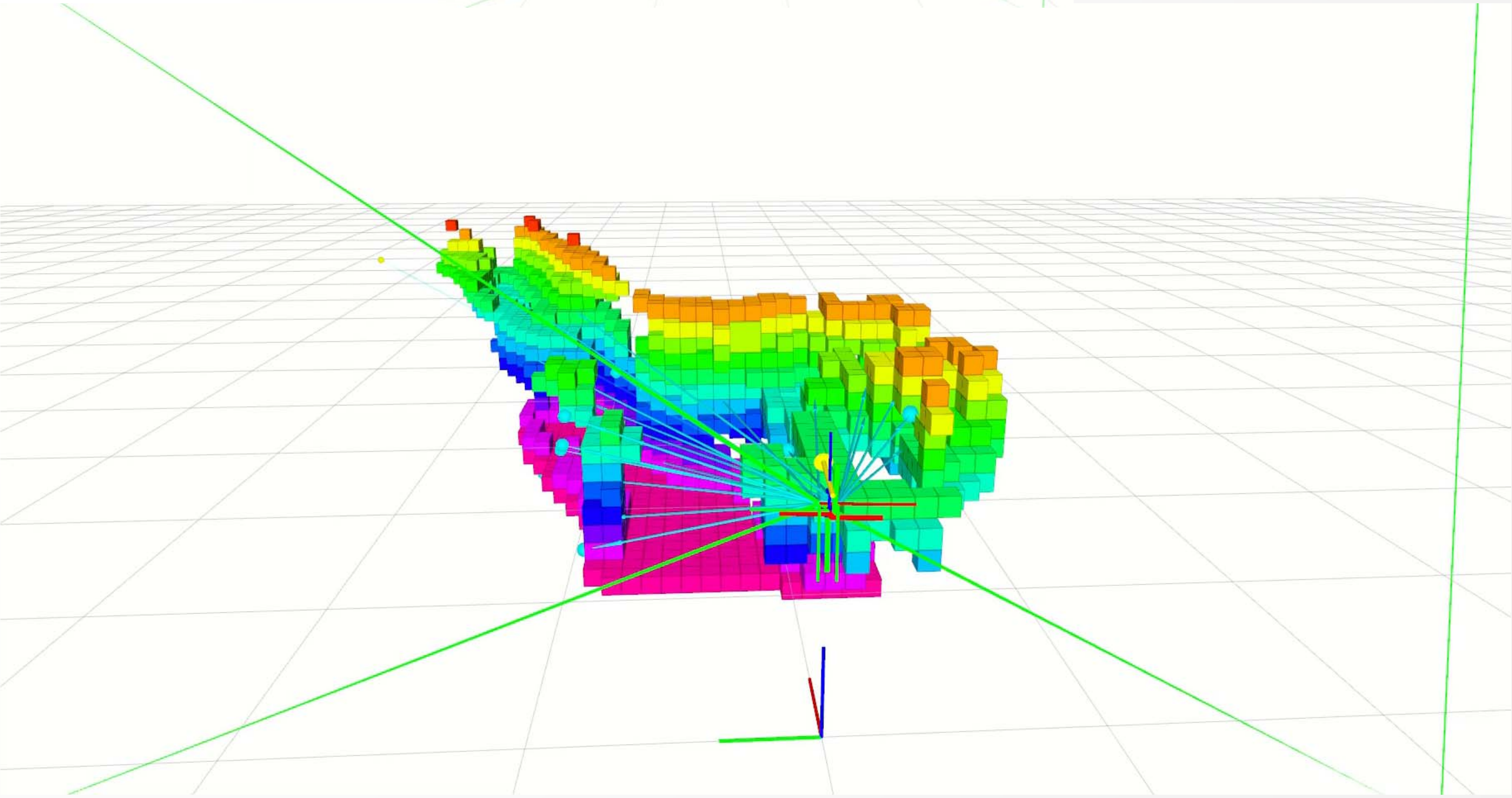
- **Path-planning:**

3D-Reconstruction and Mapping



Voxelgrid from Pointcloud (**`octomap`**)

- Volumetric representation of the known environment.
- Makes distinction between occupied & free voxels.
- Efficient representation in memory (octree structure).
- Fast node (voxel) lookup given its 3D coordinates. Allows speedy execution of checking nodes that intersect given trajectories.



Constituents of Autonomy

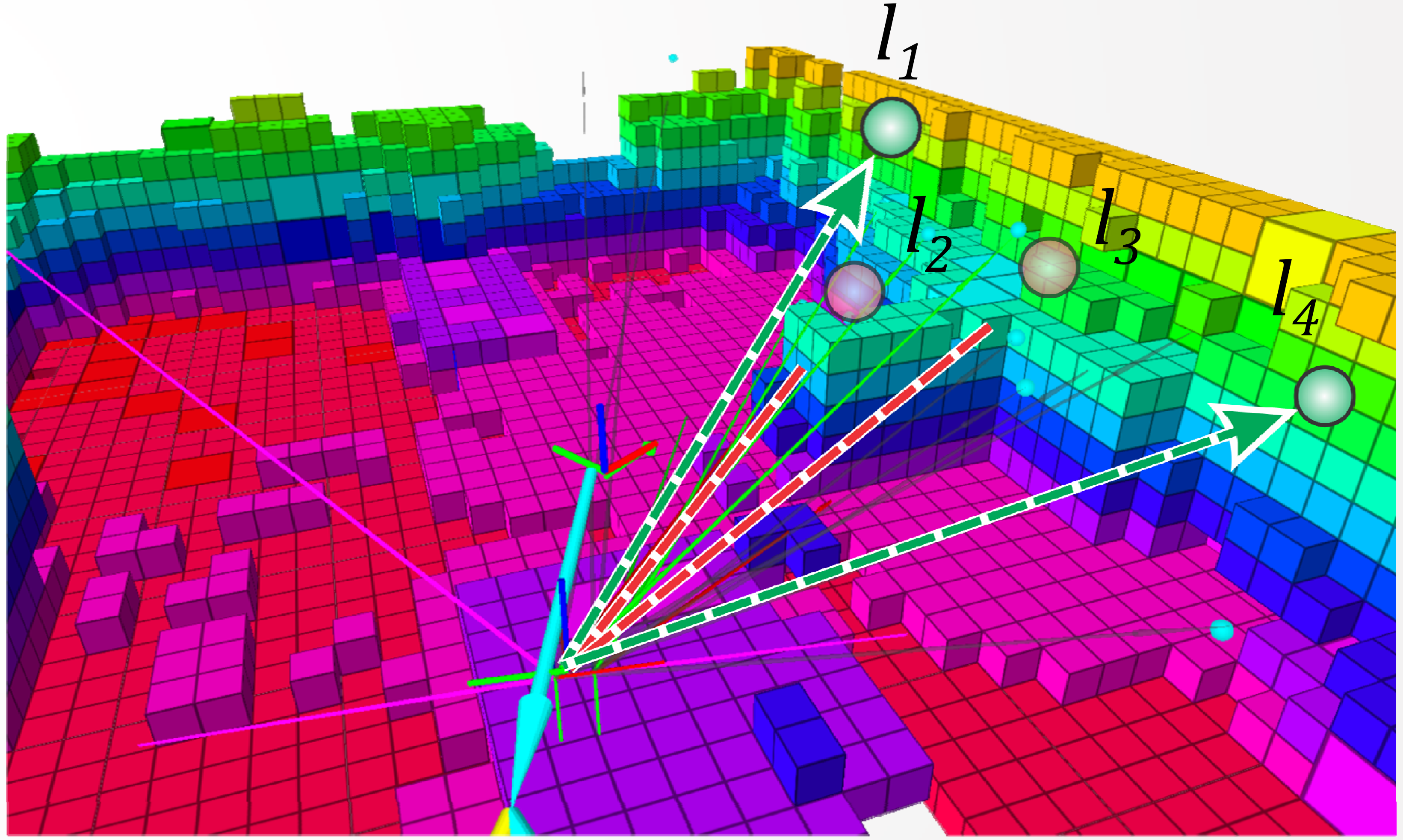
- **Path-planning:**

3D-Reconstruction and Mapping

Voxelgrid from Pointcloud (**`octomap`**)

- Ray-casting / Ray-checking is the process of checking along a 3D line segment (ray) if occupied, free, or unmapped voxels are crossed.
- Checking if a transition from initial 3D configuration to a desired one (waypoint) will encounter an obstacle.
- Checking if a 3D landmark lies in Line-of-Sight or "blocked".
- etc…

Ray collision checks for landmark visibility



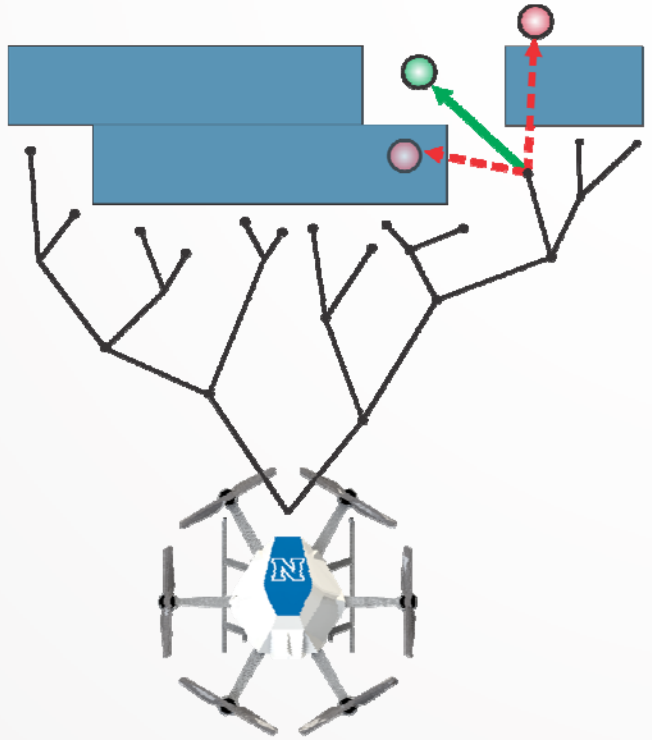
Constituents of Autonomy

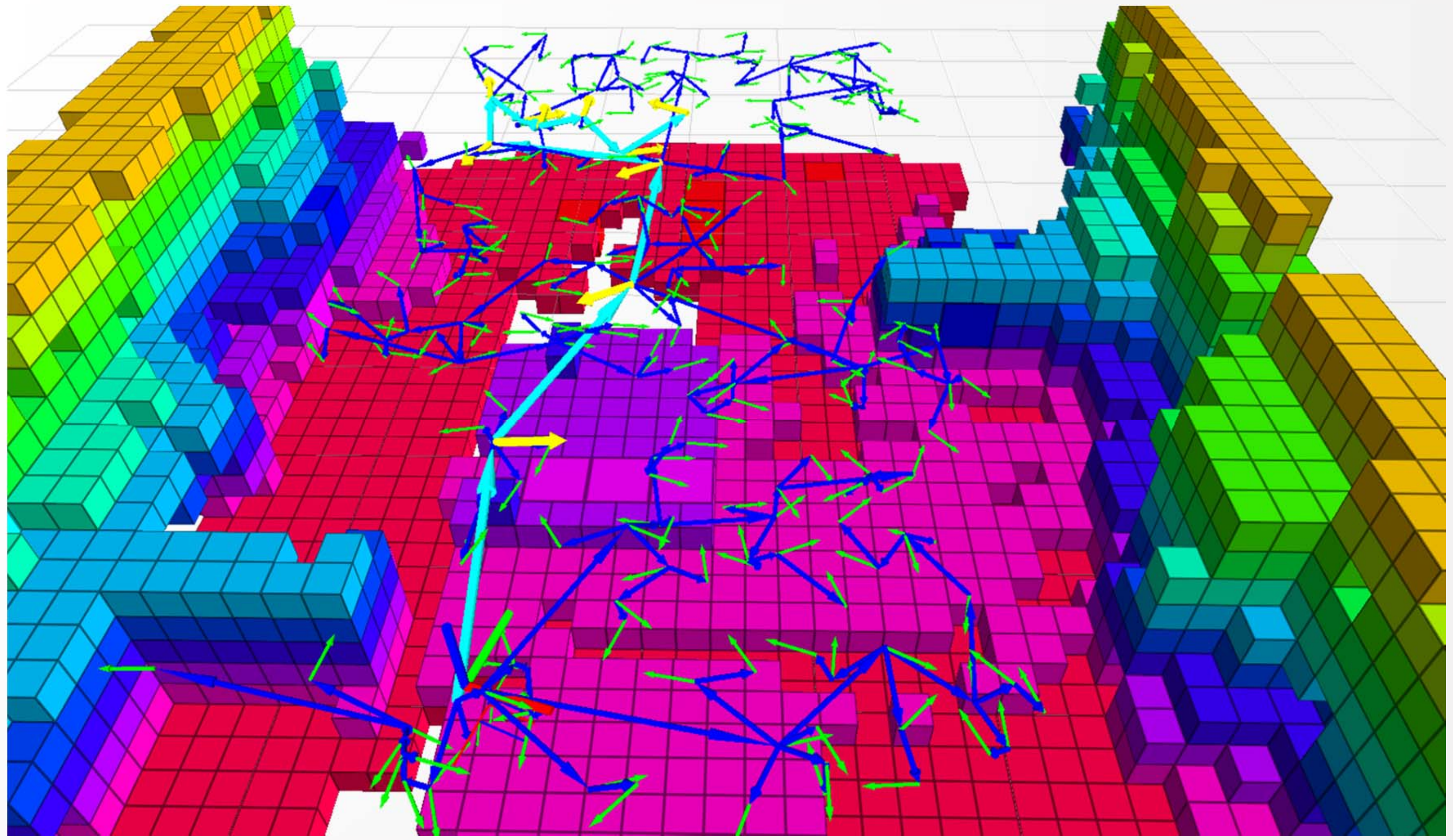
- **Core Path-planning Principles:**

Random Sampling

Expanding Random Trees in the known (mapped) and free configuration space.

- Only Collision-free transitions are permitted for every segment.
- Collision-free navigation along path.



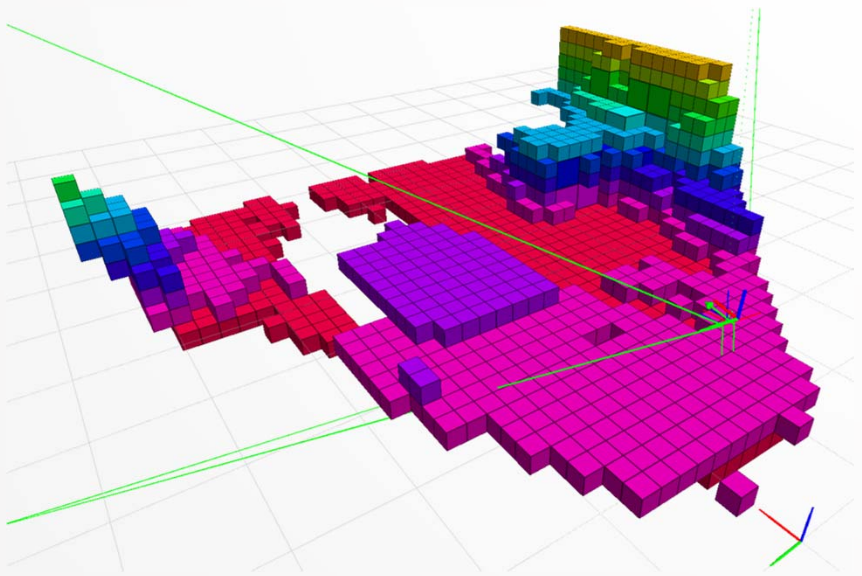
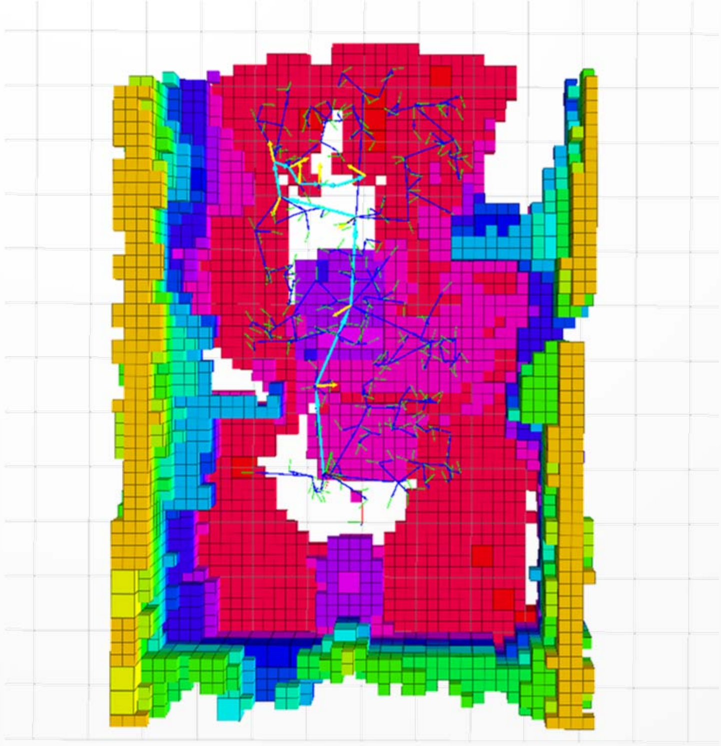
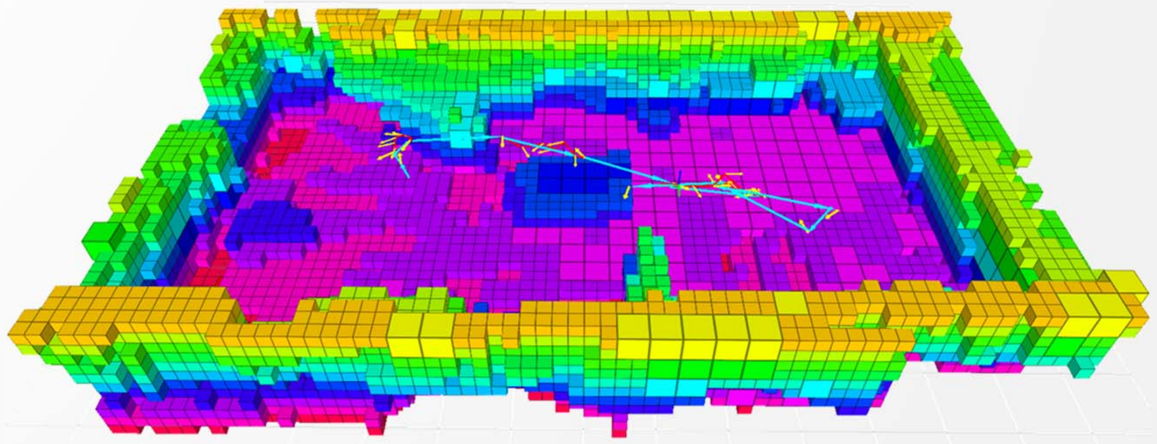


Constituents of Autonomy

- **Core Path-planning Principles:**

  Receding Horizon approach

  - A finite number of path-planning moves (e.g. the first segment only) is performed.
  - Real-time feedback from Mapping updates the environment knowledge. Based on this updated state, path-planning is re-evaluated.
  - The first moves is performed again, with each iteration followed by a new map update.

Constituents of Autonomy

- **The Objective:**

Autonomously explore a previously unknown location.

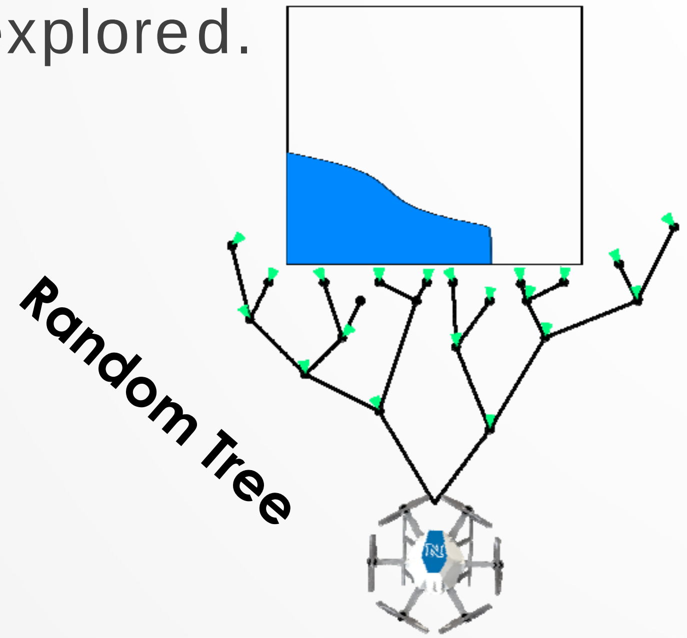
Problem Definition: Volumetric Exploration
The exploration path planning problem consists in **exploring a previously unknown bounded 3D space** $V \subset \mathbb{R}^3$. This is to determine which parts of the initially unmapped space $V_{unm} = V$ are free $V_{free} \subset V$ or occupied $V_{occ} \subset V$. 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.

Constituents of Autonomy

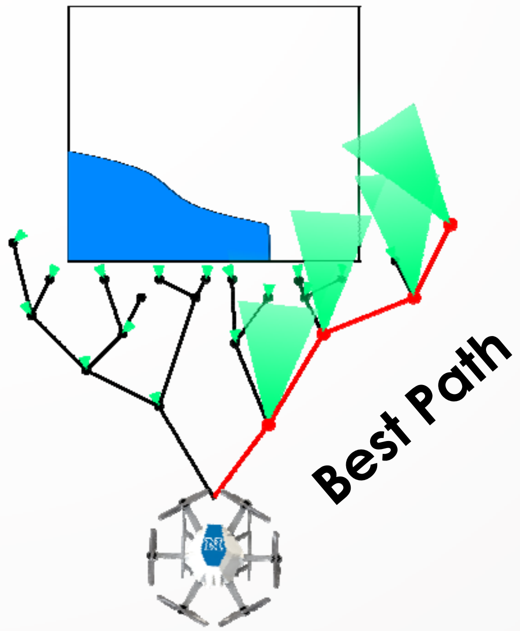
- **Autonomous Volumetric Exploration:**

  Next-Best-View Pathplanner (`nbvplanner`)

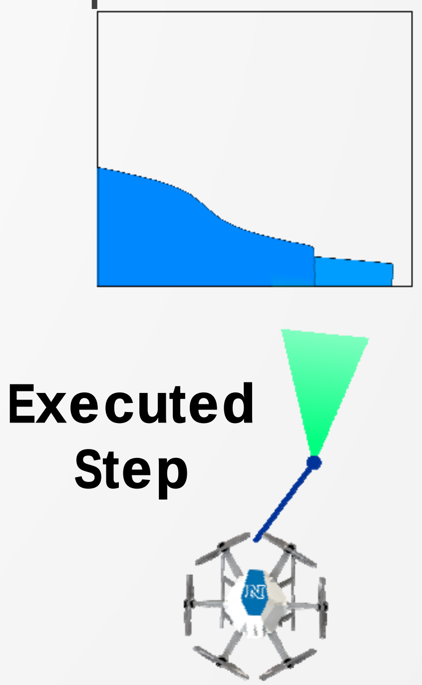
- **Tree-based exploration:** At every iteration, a finite depth random tree is spanned. Each vertex is annotated with the collected Information Gain – a metric of how much new space is going to be explored.



- Within it, evaluation regarding the path that overall leads to the highest information gain is conducted. This corresponds to the **best path** for the given iteration (a sequence of next-best-views as sampled).



- **Receding Horizon:** For the extracted best path, only the first viewpoint is actually executed.
- The system moves to it, map is updated, process is repeated.



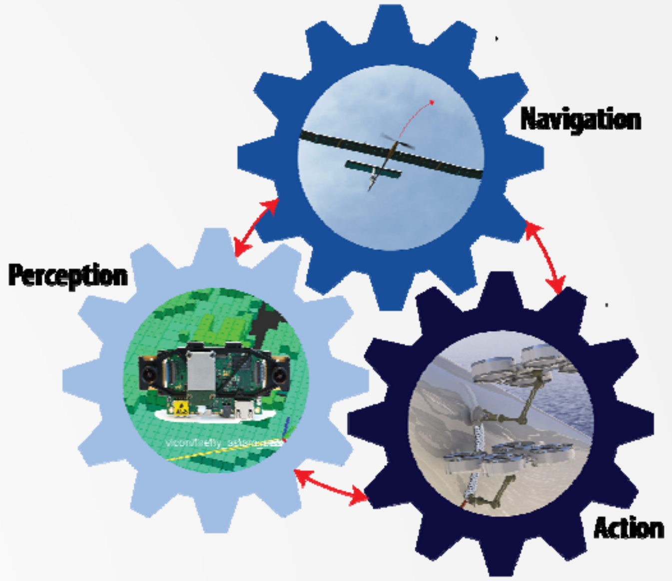
$$\textbf{Gain}(n_k) = \textbf{Gain}(n_{k-1}) + \textbf{Visible}(\mathcal{M}, \xi_k)e^{-\lambda c(\sigma_{k-1}^k)}$$

Constituents of Autonomy

- **Autonomous Volumetric Exploration:**

  Next-Best-View Pathplanner (`nbvplanner`)

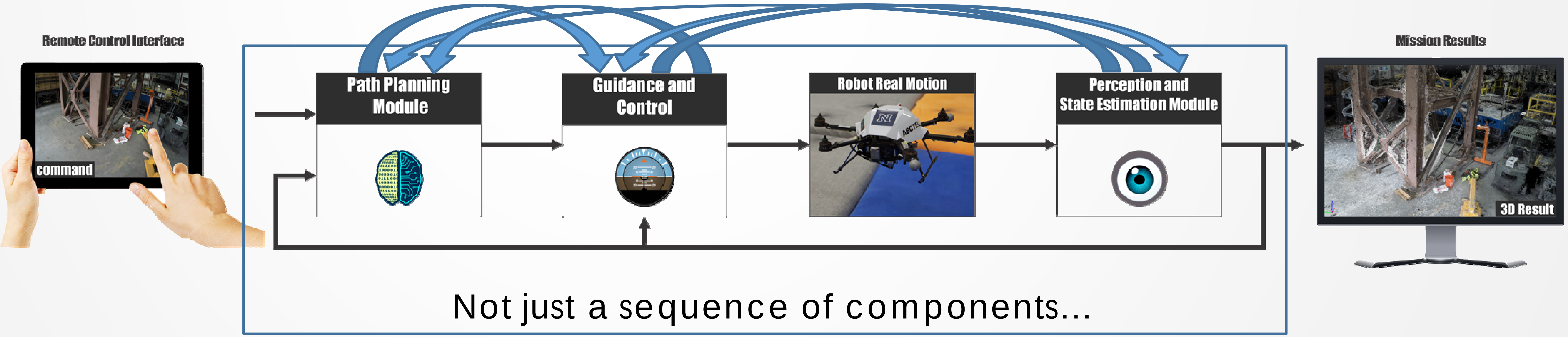
Advancing Autonomy



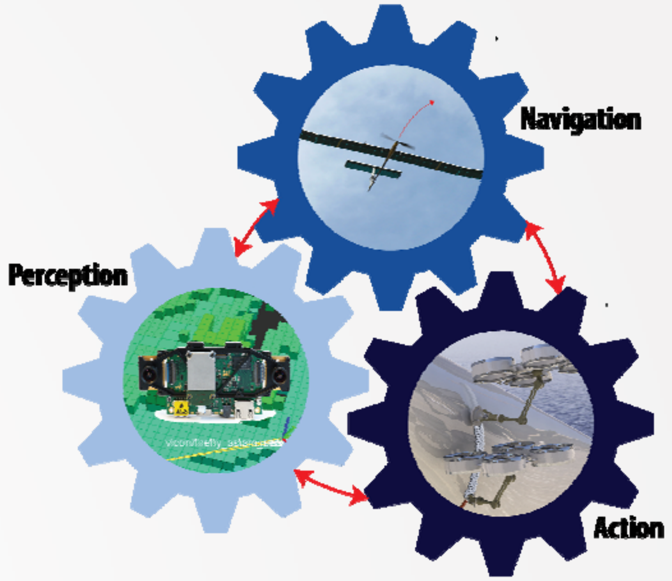
- **Synergies & Aliases between Autonomy Components:**

  Perception, Control, Path-planning can be coupled.

- Investigate new ways to close the loop between perception, planning and control.
- Estimation robustness affects control. Jerky control impacts state estimation. Collision free navigation requires robust control. Large-scale planning requires globally consistent mapping. Efficient precision planning has to keep track of mapping uncertainty.



Advancing Autonomy

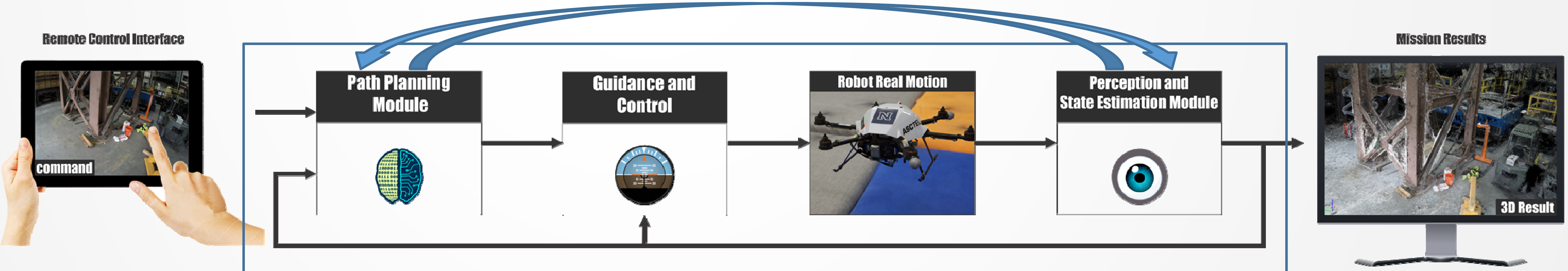


- **Synergies & Aliases between Autonomy Components:**

  Perception, Control, Path-planning can be coupled.

Active Perception Planning

- Robustify the exploration and mapping process by exploiting propagation of robot belief.



Not just a sequence of components...

Advancing Autonomy

- **The Objective:**

Explore and map a location with consistency.

Problem Definition
The overall problem is that of **exploring an unknown bounded 3D volume $V^E \subset \mathbb{R}^3$**, **while aiming to minimize the localization and mapping uncertainty** as evaluated through a metric over the robot pose and landmarks **probabilistic belief**.

Combined Problem

Problem 1: Volumetric Exploration
Given a bounded volume V^E, find a collision free path σ starting at an initial configuration $\xi_{init} \in \Xi$that leads to identifying the free and occupied parts V^E_{free} and V^E_{occ} when being executed, such that there does not exist any collision free configuration from which any piece of $V^E\{V^E_{free}, V^E_{occ}\}$ could be perceived.

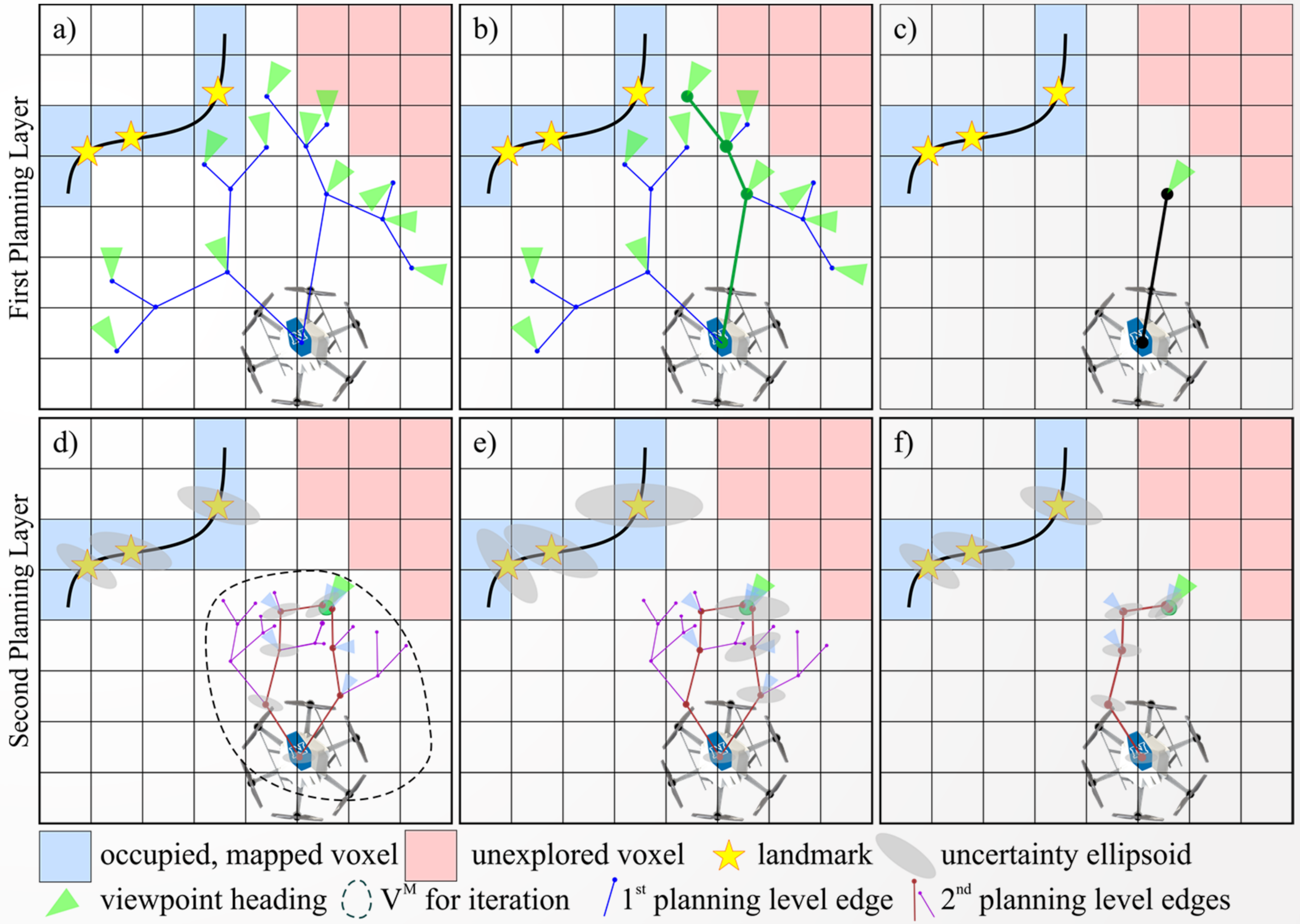
Problem 2: Belief Uncertainty-aware planning
Given a $V^M \subset V^E$, find a collision free path σ^M starting at an initial configuration $\xi_0 \in \Xi$ and ending in a configuration $\xi_{final} \in \Xi$ that aims to improve the robot's localization and mapping confidence by following paths of optimized expected robot pose and tracked landmarks covariance.

Advancing Autonomy

Autonomous Uncertainty-Aware Exploration & Mapping

Receding-Horizon-Exploration Mapping Path-planner (`rhemplanner`)

- **Two-level Path-planning paradigm:** Addresses the combined problem every iteration, a finite depth random tree is spanned. Each vertex is annotated with the collected Information Gain – a metric of how much new space is going to be explored.



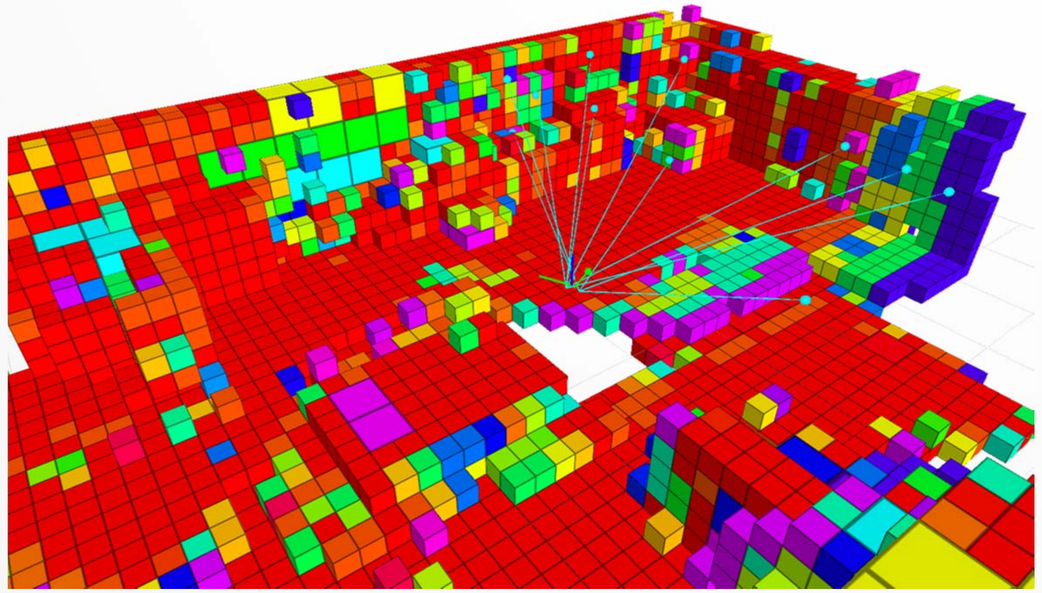
Advancing Autonomy

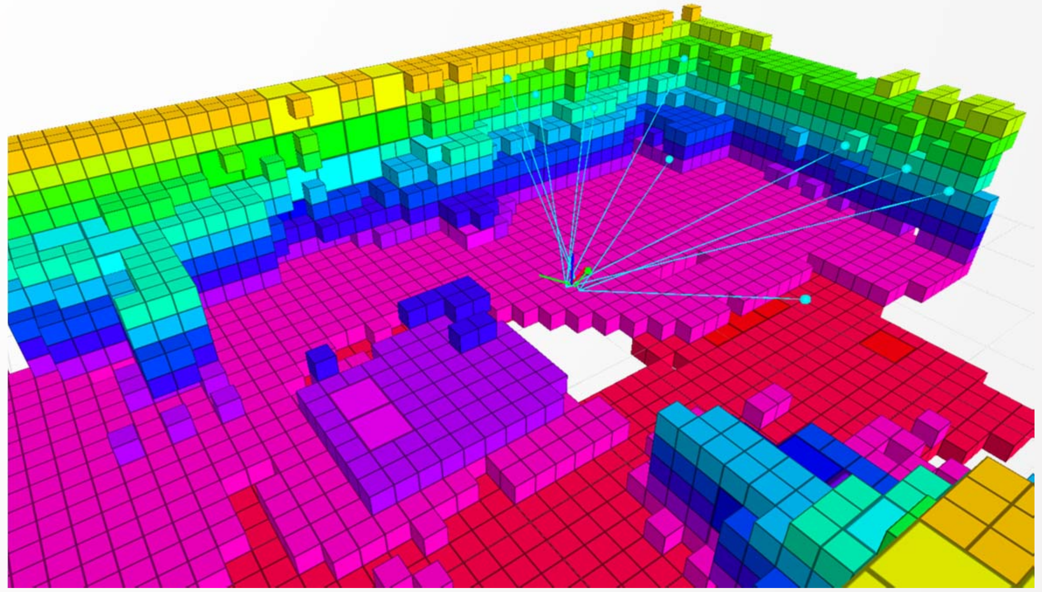
- **Autonomous Uncertainty-Aware Exploration & Mapping**

  Exploration Level

  - Probabilistic Re-observation term: Maximize newly explored space and re-observe the parts where confidence whether they are occupied is decreased.

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



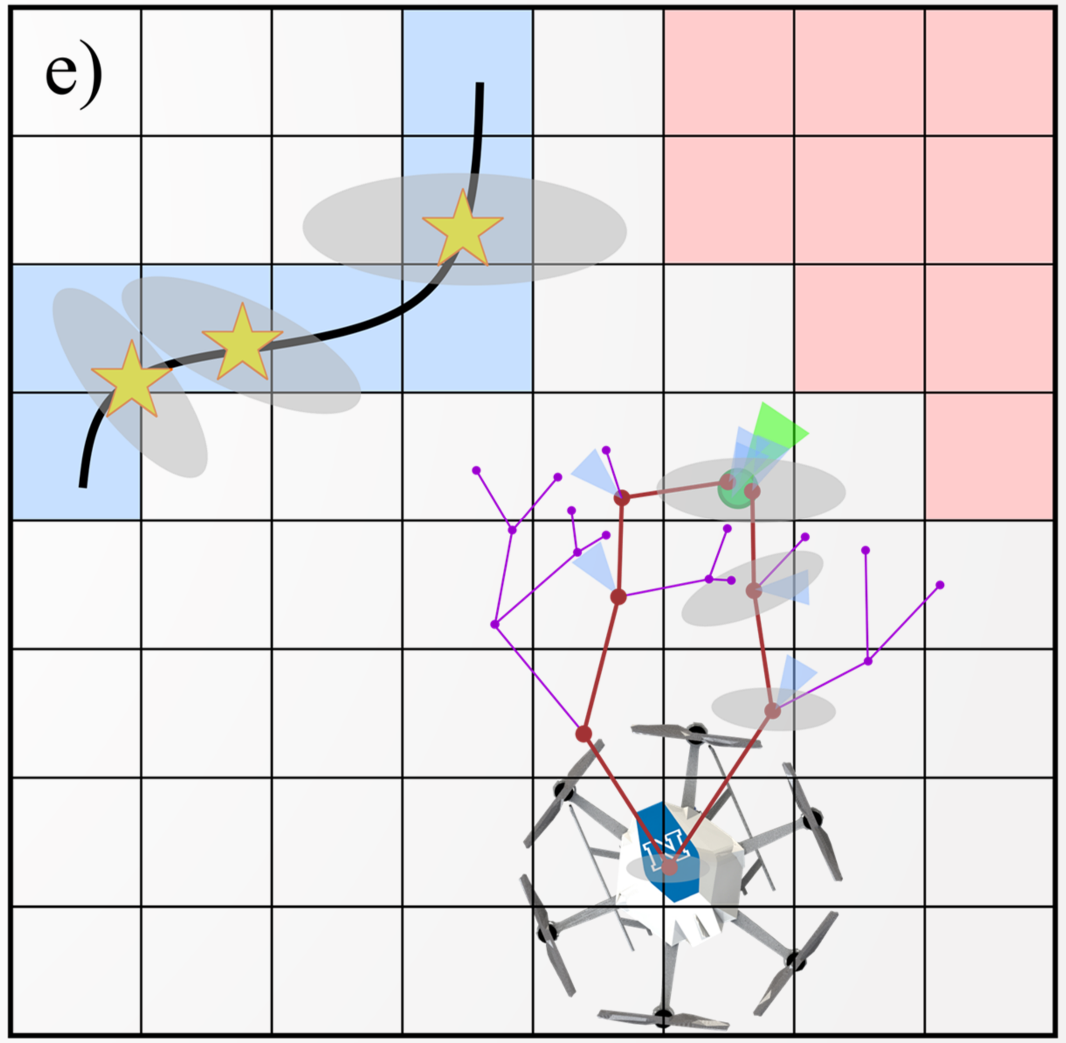


Advancing Autonomy

- **Autonomous Uncertainty-Aware Exploration & Mapping**

  Uncertainty-Aware Level

  - Evaluation of a path that minimizes the robot localization uncertainty.
  - Pose and the tracked landmarks' uncertainty are estimated while performing real-time odometry.
  - The mechanism to propagate robot's belief has to be established.

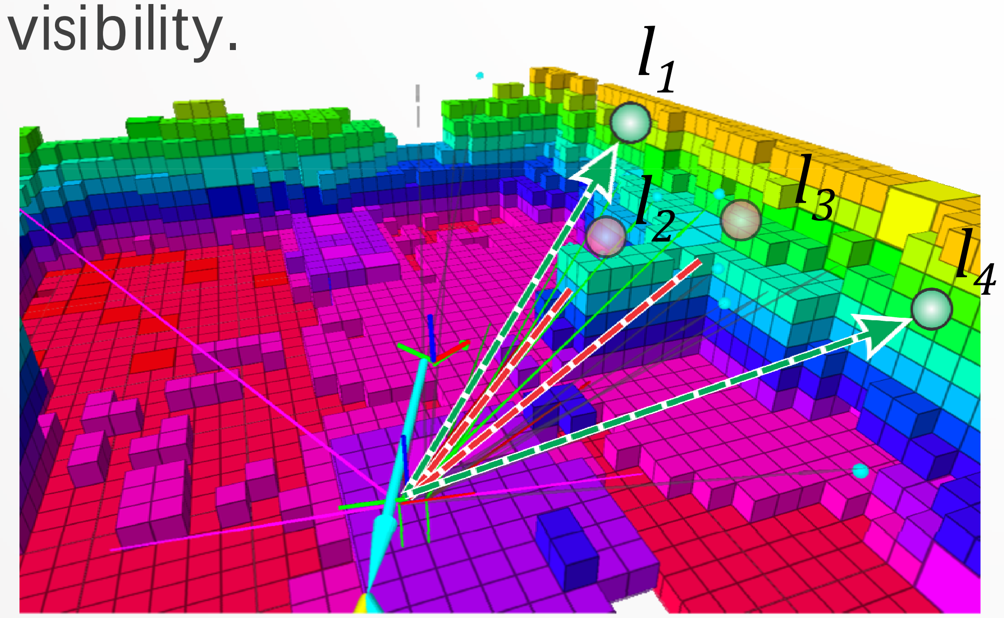


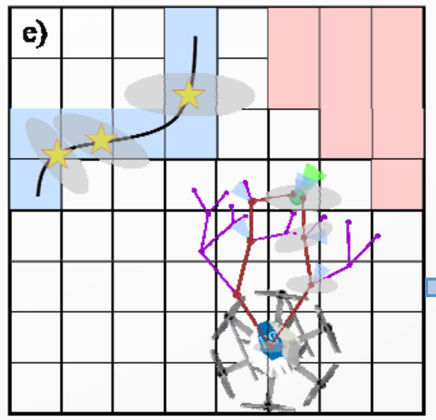
Advancing Autonomy

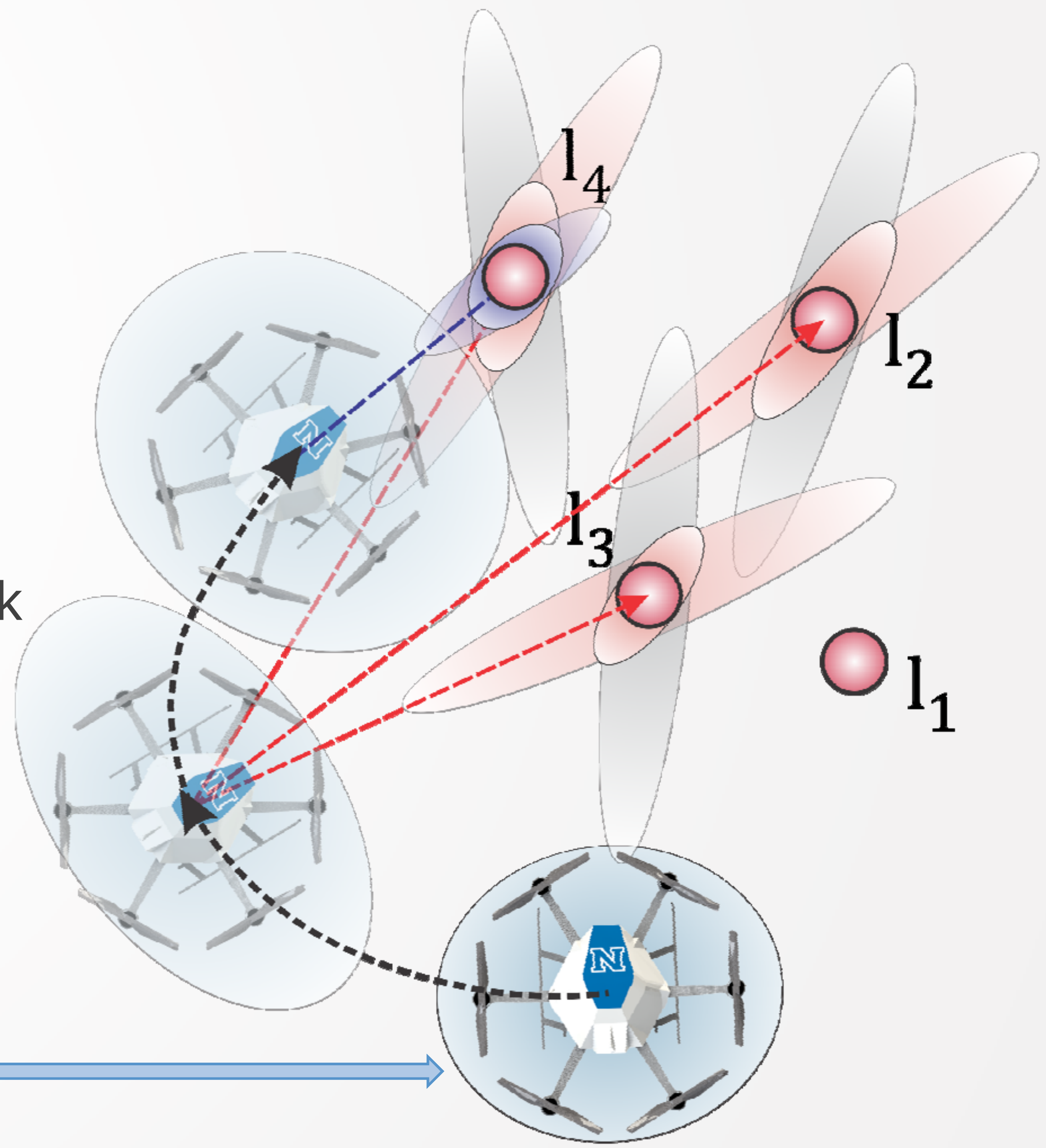
- **Autonomous Uncertainty-Aware Exploration & Mapping**

Uncertainty-Aware Level

- Use the EKF-based mechanism that provides localization backend to propagate own pose and landmarks' belief.
- Assume closed-loop system dynamics model as identified – simulated inertial measurements.
- Augment with `octomap`-support to compute landmark visibility.





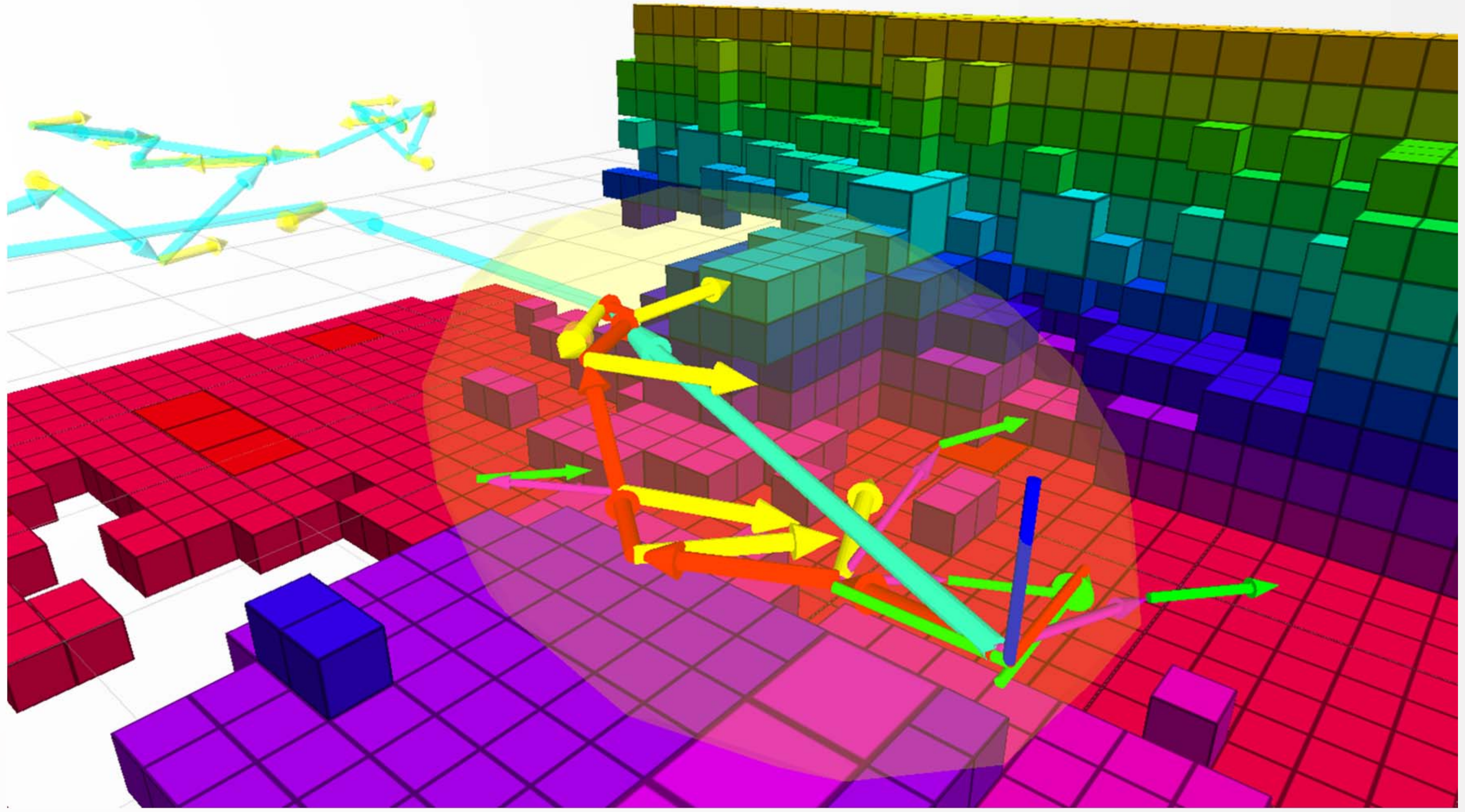


Advancing Autonomy

- **Autonomous Uncertainty-Aware Exploration & Mapping**

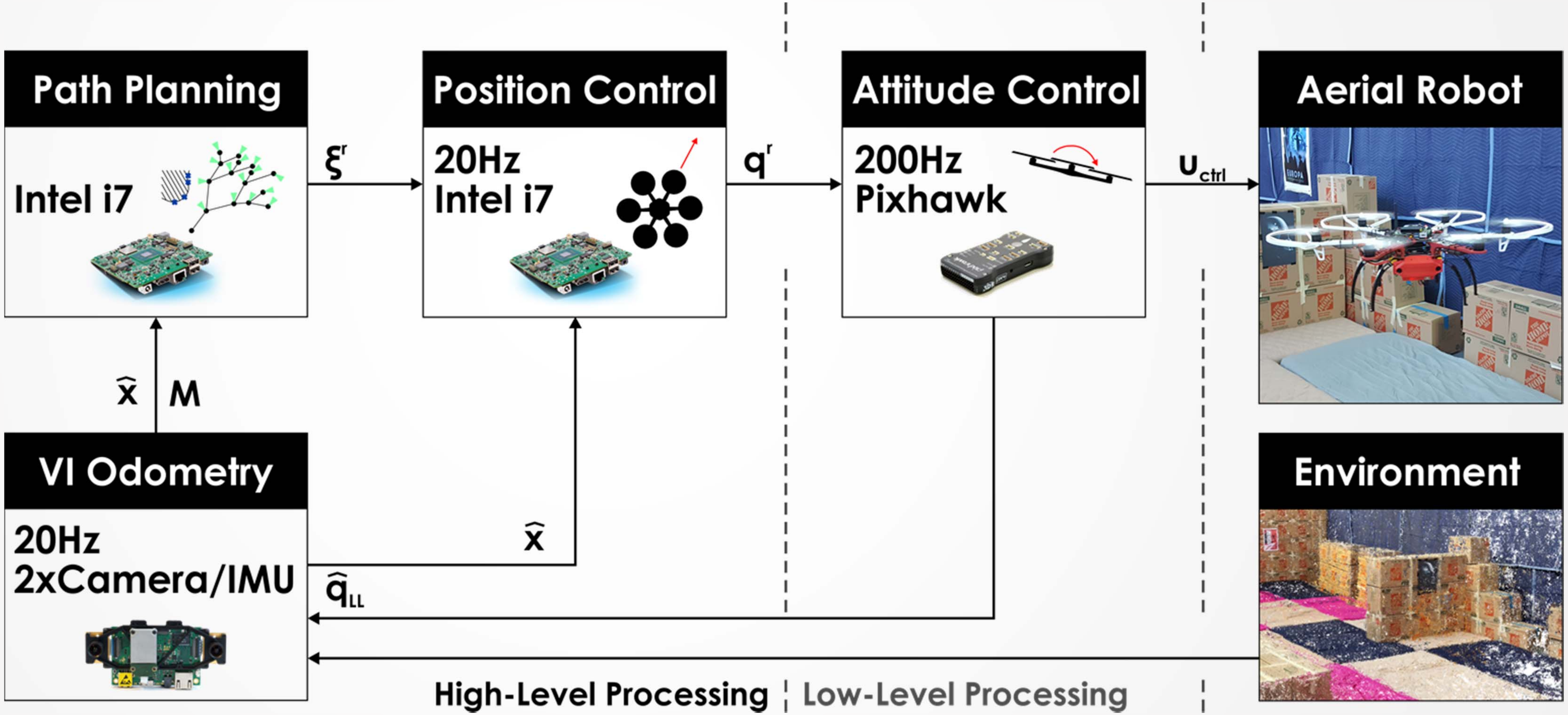
Uncertainty-Aware Level

- Finally, the path that arrives at the Exploration Level's end viewpoint with the minimal uncertainty is selected.
- The *D-optimality* metric of the propagated process covariance matrix is used.
- This path might turn out to be the original straight segment – Optimum is only selected out of a finite number of randomly sampled trajectories.



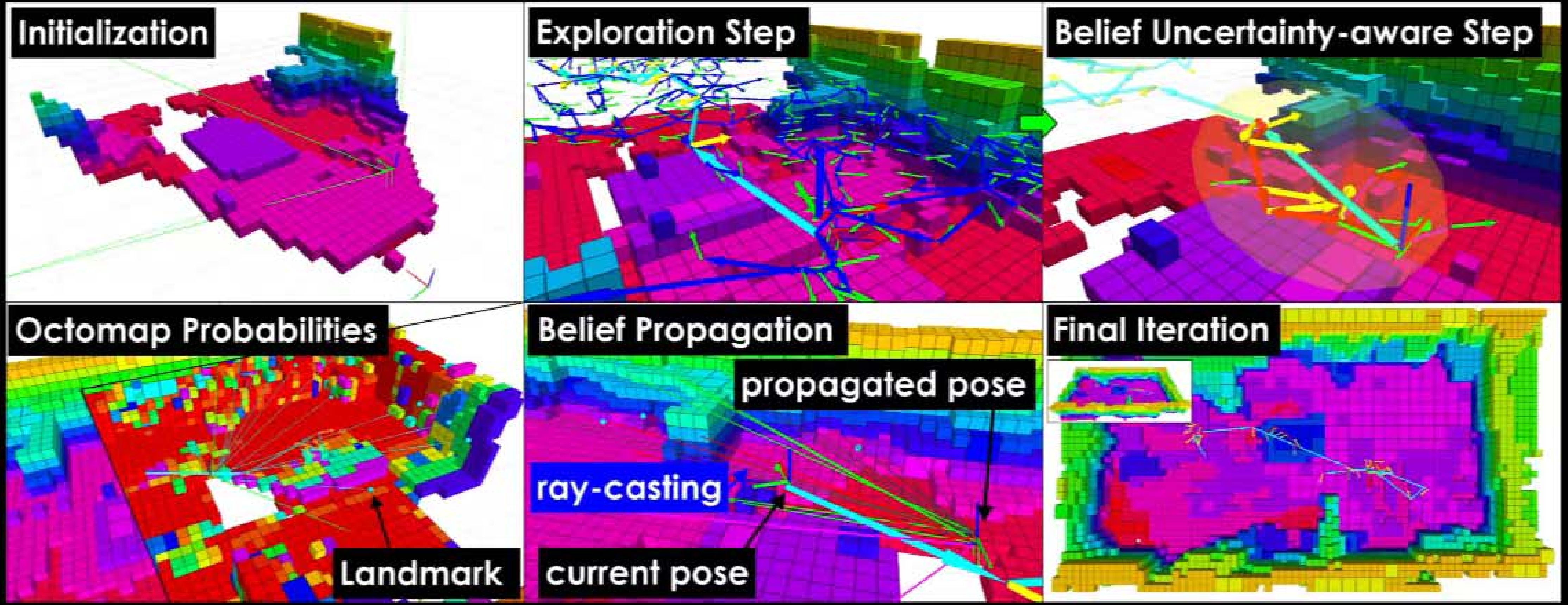
Experimental Evaluation

- **Receding-Horizon Exploration Mapping Pathplanner** (`rhemplanner`)



Uncertainty-aware Receding Horizon Exploration and Mapping using Aerial Robots

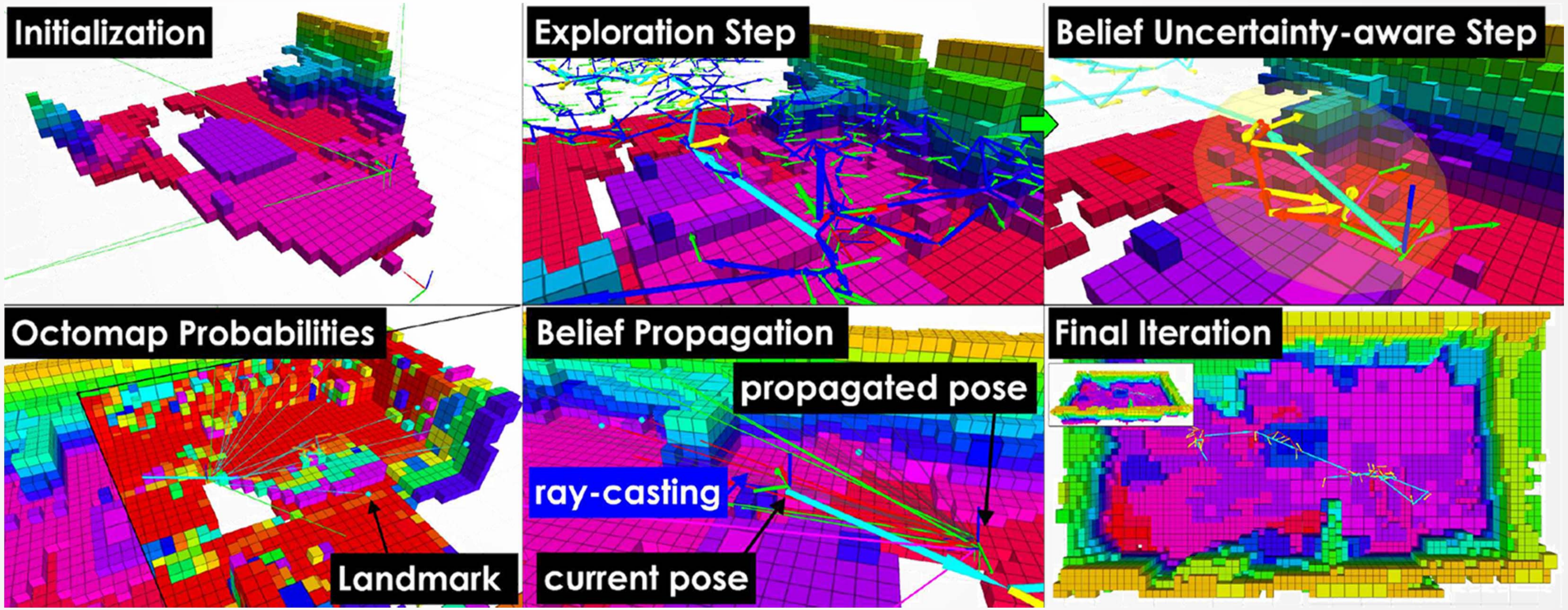
Christos Papachristos, Shehryar Khattak, Kostas Alexis



AUTONOMOUS ROBOTS LAB

Experimental Evaluation

- **Receding-Horizon Exploration Mapping Pathplanner** (`rhemplanner`)



Experimental Evaluation

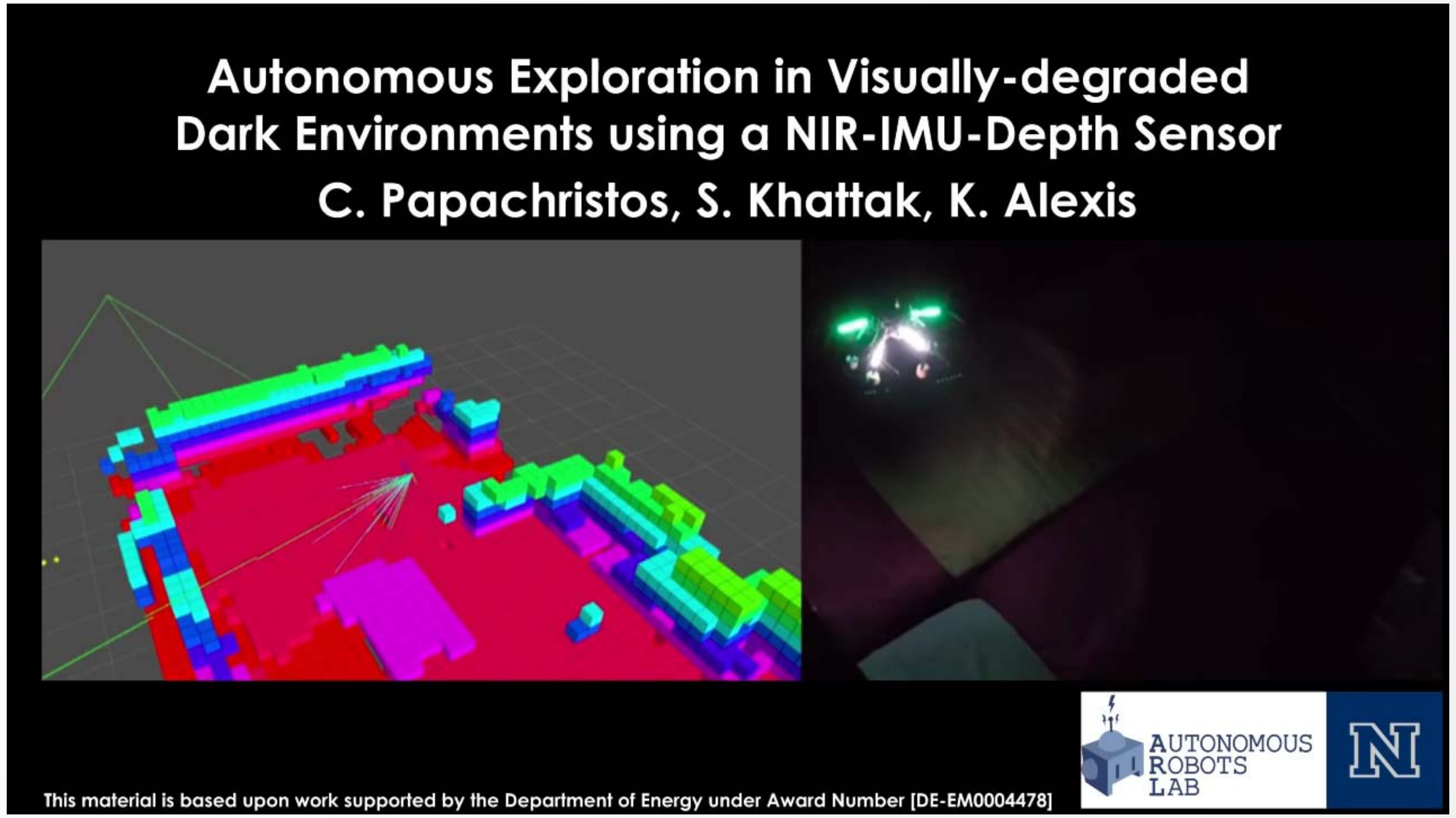
- **Receding-Horizon Exploration Mapping Pathplanner** (`rhemplanner`)

Current Research

- **Visually-Degraded Environments**
  - Generalizable solutions enable accelerated paces of research.

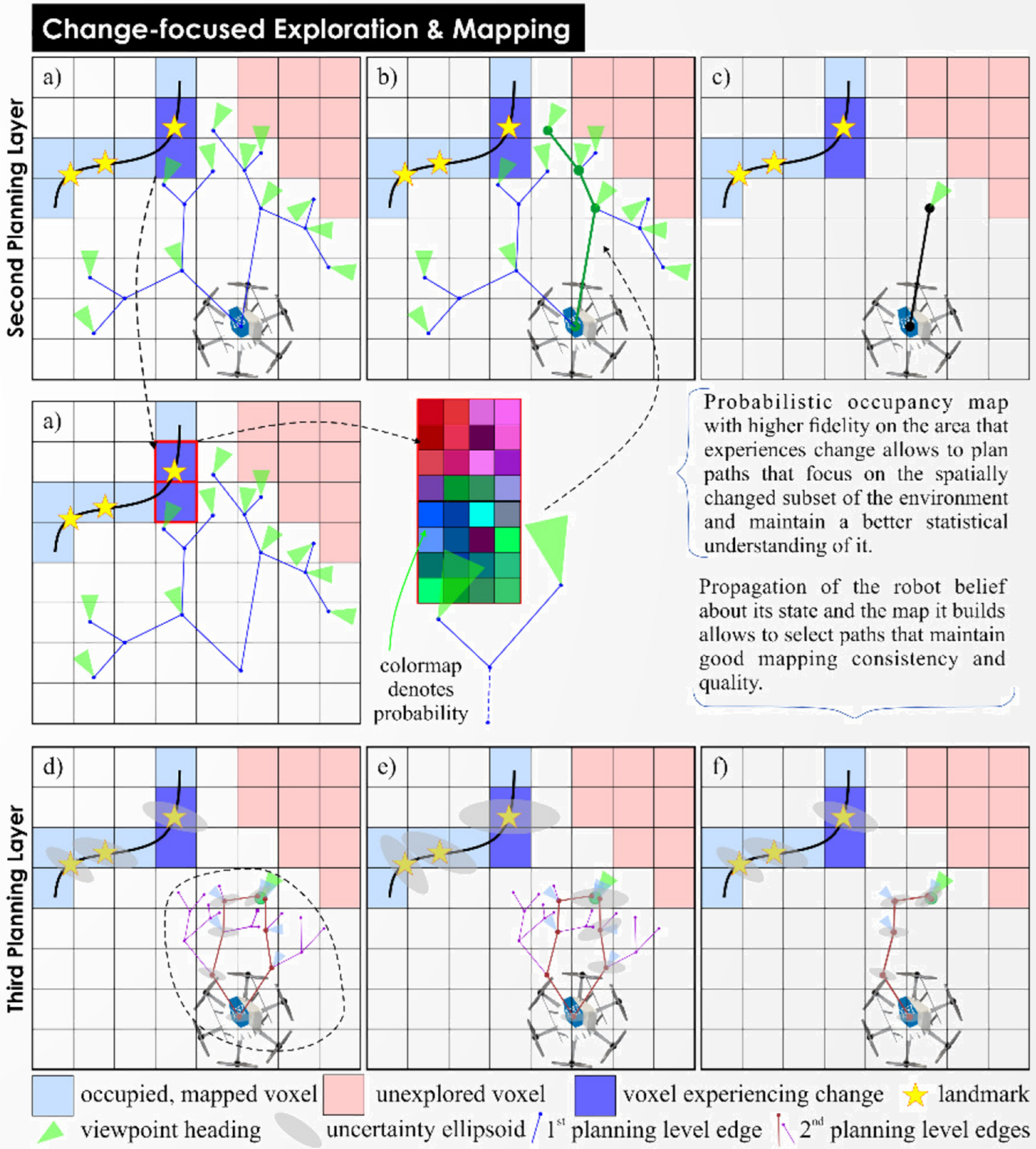
Current Research

- **Visually-Degraded Environments**
  - Generalizable solutions enable accelerated paces of research.
  - Uncertainty-Aware Exploration and Mapping in darkness.



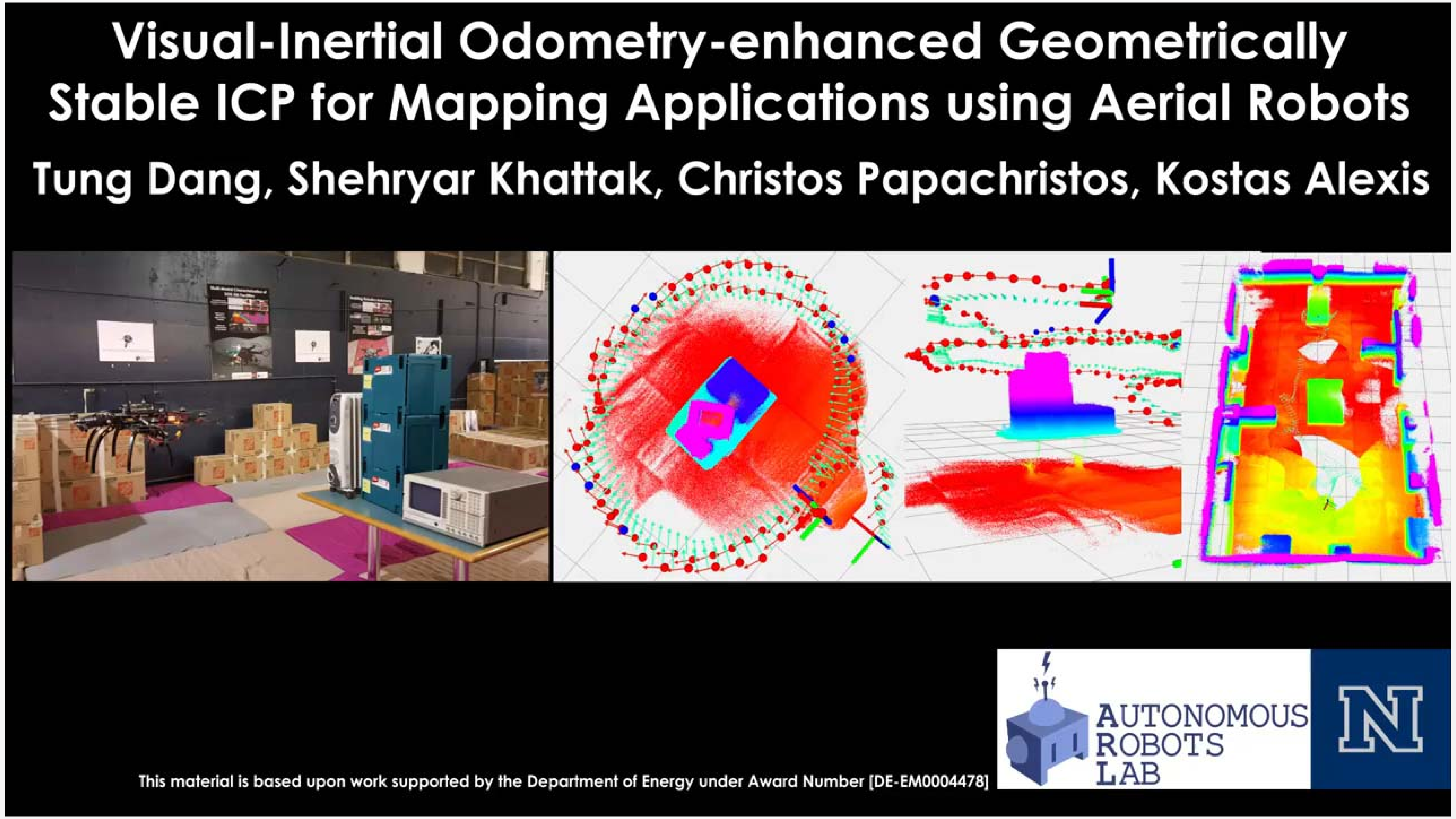
Current Research

- **Change Detection and Classification:**
  - Perform real-time change detection.
  - Expand to efficient 3D-to-3D change detection approaches.
  - Incorporate change-driven "curiosity" in planning algorithms.



Current Research

- **Multi-Modal Sensor Fusion**
  - Robustify autonomous localization & mapping. Augment uncertainty-aware path-planning.



Thank you!

Please ask your question!