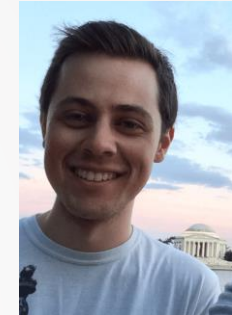




The Autonomous Robots Lab

Kostas Alexis

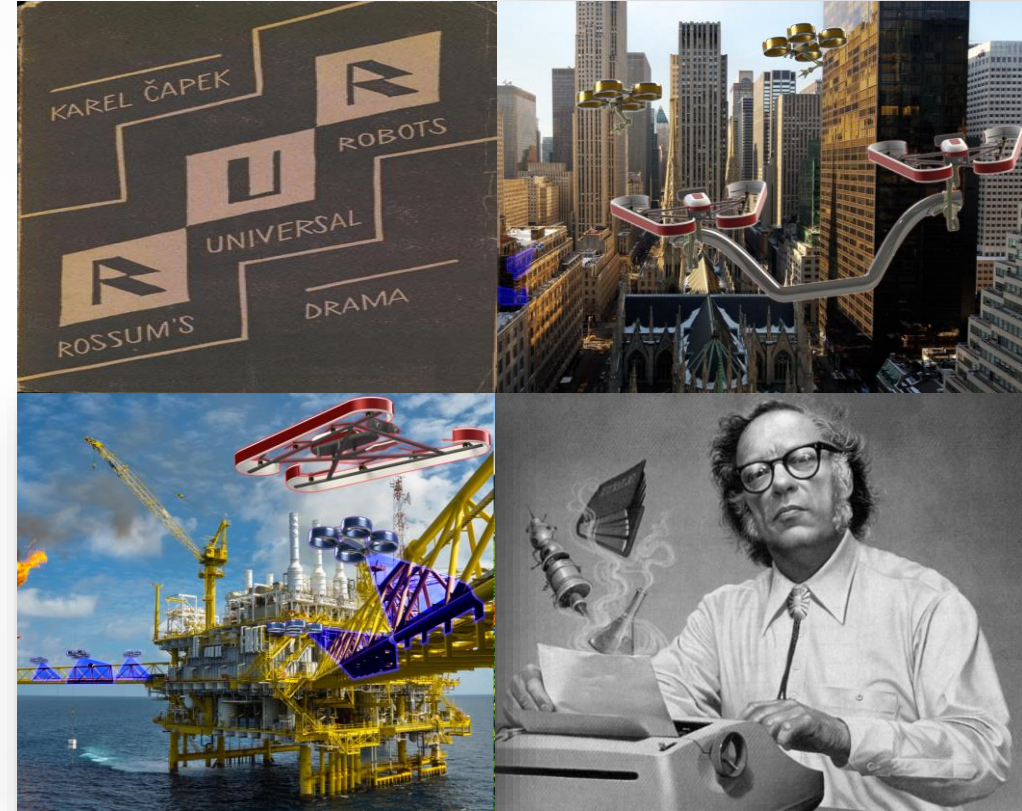
Who we are?



- Established at January 2016
- **Current Team:** 1 Head, 1 Senior Postdoctoral Researcher, 3 PhD Candidates, 1 Graduate Research Assistant, 2 Undergraduate Researchers
- **From summer 2017:** 1 more Senior Postdoctoral Researcher and 1 more PhD Candidate

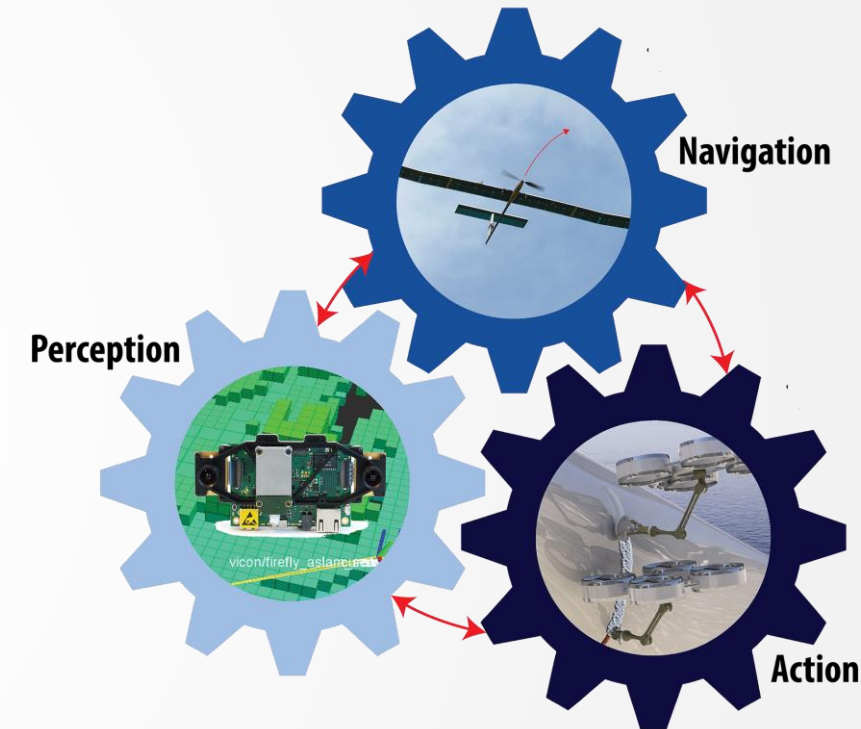
What's our vision?

- From Capek's "**R.U.R.**" to Asimov's "**Robot Visions**", robots are considered perfected workers. Either in dystopic or utopic future projections, humanity has envisioned the dream of a robotized world, a world that work is conducted by robots. **How far away are we?**
- Robotics can assist societal needs for sustainable and scalable growth, quality of life, scientific exploration and more. Given that we deal with the challenges involved.
- To do so in large scale, robotic systems have to be autonomous regarding their navigation, operation and task handling.
- **Autonomy is the key.** Within that, currently perception and planning are the two urgent needs.

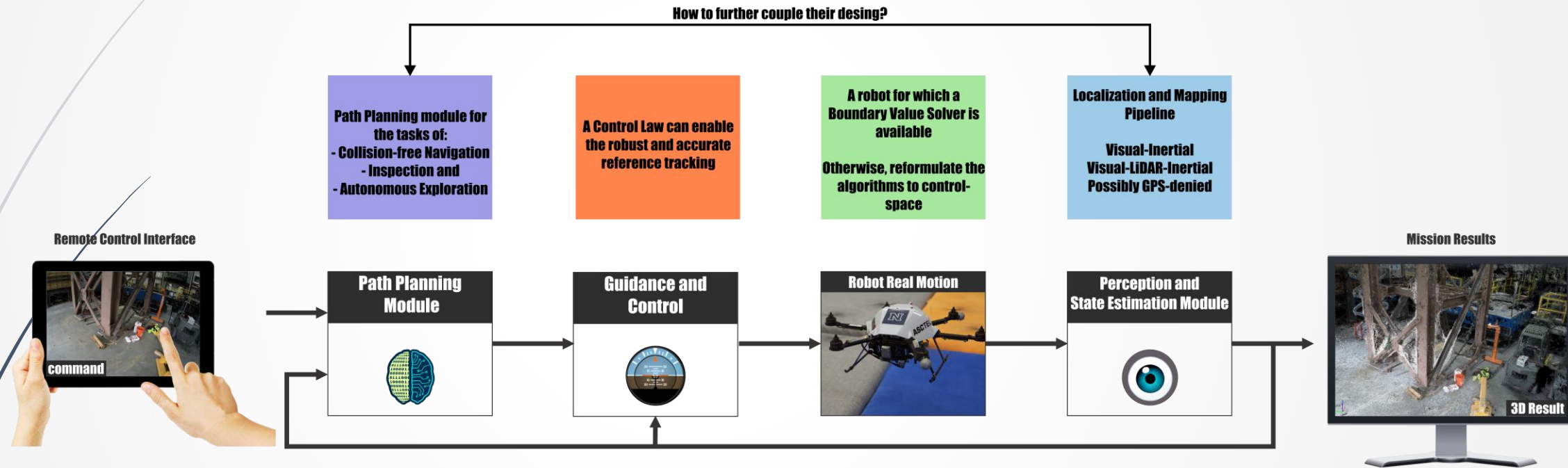


Autonomy is the Key

- An autonomous robot relies on the robust and reliable operation and interconnection of its onboard perception, planning and control loops.
- For robust autonomy we search for a tightly closed perception-planning-control loop.
- Therefore, the research of the lab focuses on these fields simultaneously and aims to investigate their correlations and interdependencies.
- Broader goal: **Robustly Autonomous Ubiquitous Robots**



Robot Configuration



Research Activities of the lab

- With the broader goal being that of robust autonomy, the specific research directions are:
- In terms of topic
 - **Autonomous Navigation, Exploration and Mapping**
 - **Multi-Modal Localization and Mapping in Visually-degraded Environments**
 - **Robust Control Systems**
- In terms of robotic systems
 - **Aerial (primarily)**
 - **Ground (intelligent transportation systems)**
 - **Maritime**
- In terms of applications
 - **Infrastructure Inspection and Monitoring**
 - **Radiation Mapping**
 - **Environmental Monitoring**
 - **Driverless car technology**
 - **...more**

Exploration and Mapping in Visually-degraded Environments Preliminary results

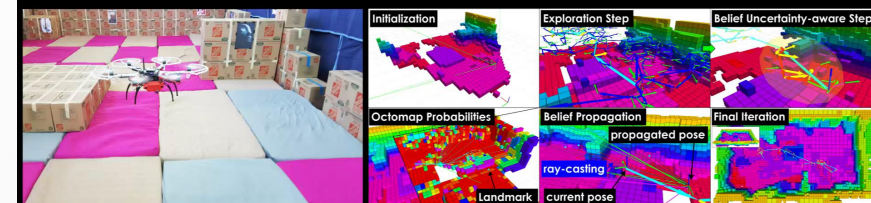
C. Papachristos, S. Khattak, F. Mascarich, K. Alexis



This material is based upon work supported by the Department of Energy under Award Number [DE-EM0004478]

Uncertainty-aware Receding Horizon Exploration and Mapping using Aerial Robots

Christos Papachristos, Shehryar Khattak, Kostas Alexis

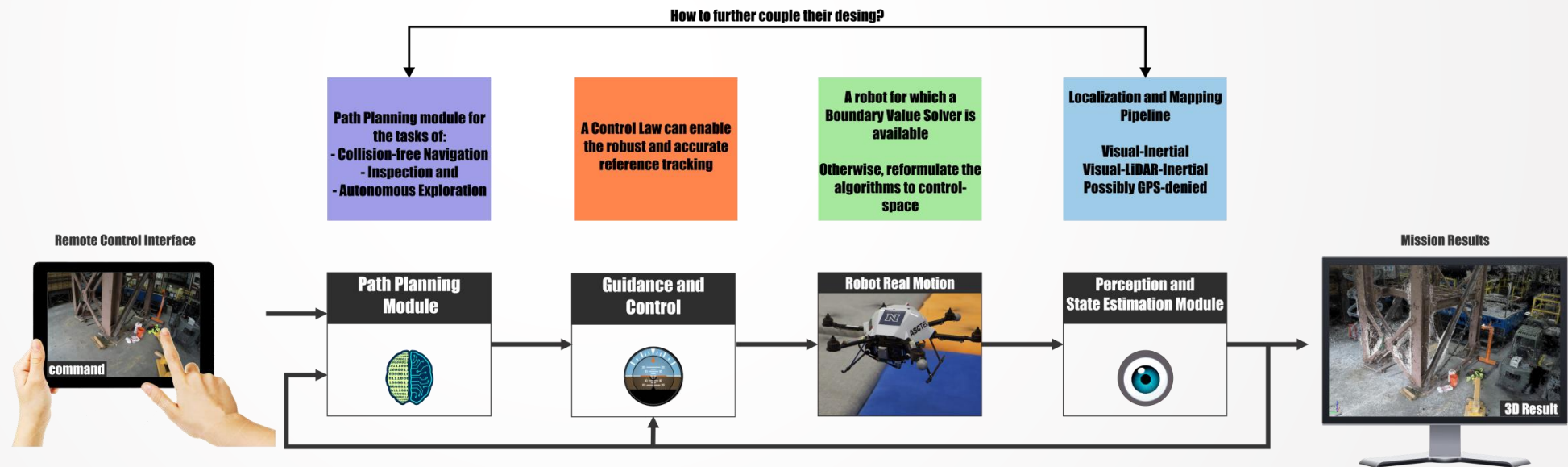


Autonomous Aerial Robots: an example

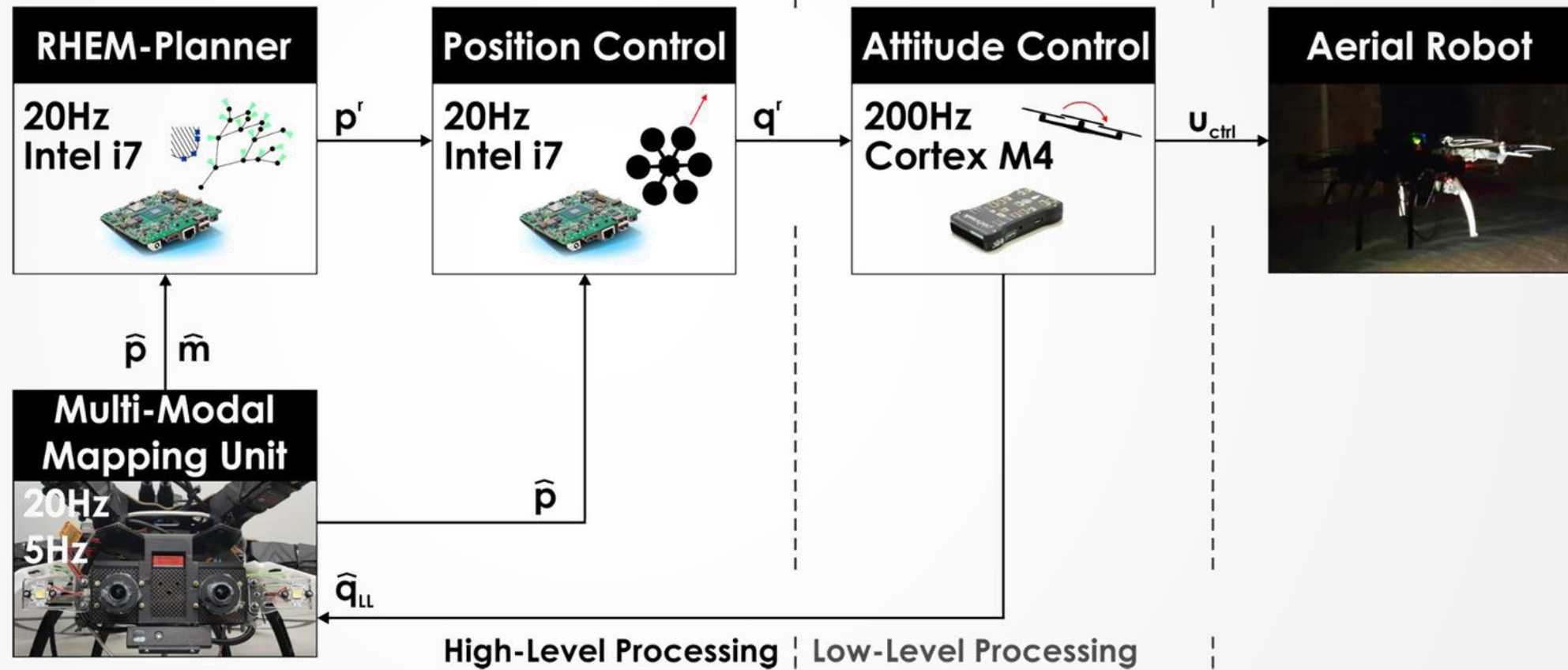
- ▶ **The Problem:** An aerial robot is requested to enter an unknown environment, explore and 3D map it, detect radiation in it and provide the end result to the user. The environment is visually-degraded and geometrically complex.

Autonomous Aerial Robots: an example

- **The Problem:** An aerial robot is requested to enter an unknown environment, explore and 3D map it, detect radiation in it and provide the end result to the user. The environment is visually-degraded and geometrically complex.
- A combined perception, planning and control problem.

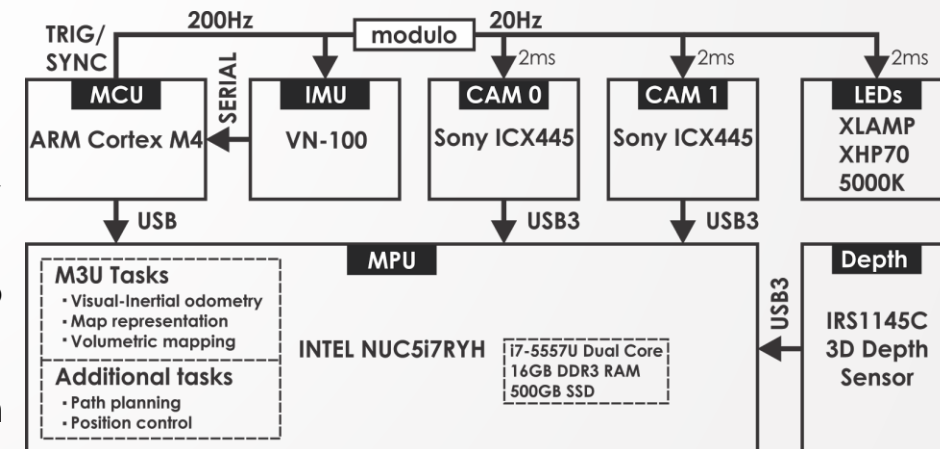
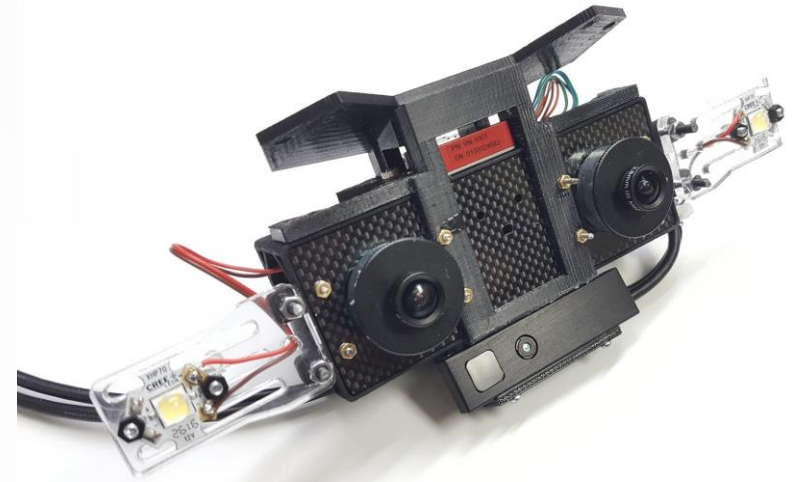


Perception – Planning – Control



Multi-Modal Localization And Mapping

- **Multi-Modal Sensor Fusion for GPS-denied operation in Degraded Visual Environments**
 - Camera systems
 - LiDAR/ToF 3D Cameras
 - Inertial sensors
- **System Optimization**
 - Hardware synchronization for reliable sensor data association
 - Sensor intrinsics and extrinsics calibration
- **Robust Multi-Modal Localization And Mapping**
 - Accurate data association [camera-to-camera, camera-to-LiDAR]
 - Robust state estimation of the robot pose and the map of the environment
 - Multi-modal sensor fusion that tracks the information matrix of the system allows reliable operation in visually-degraded environments.



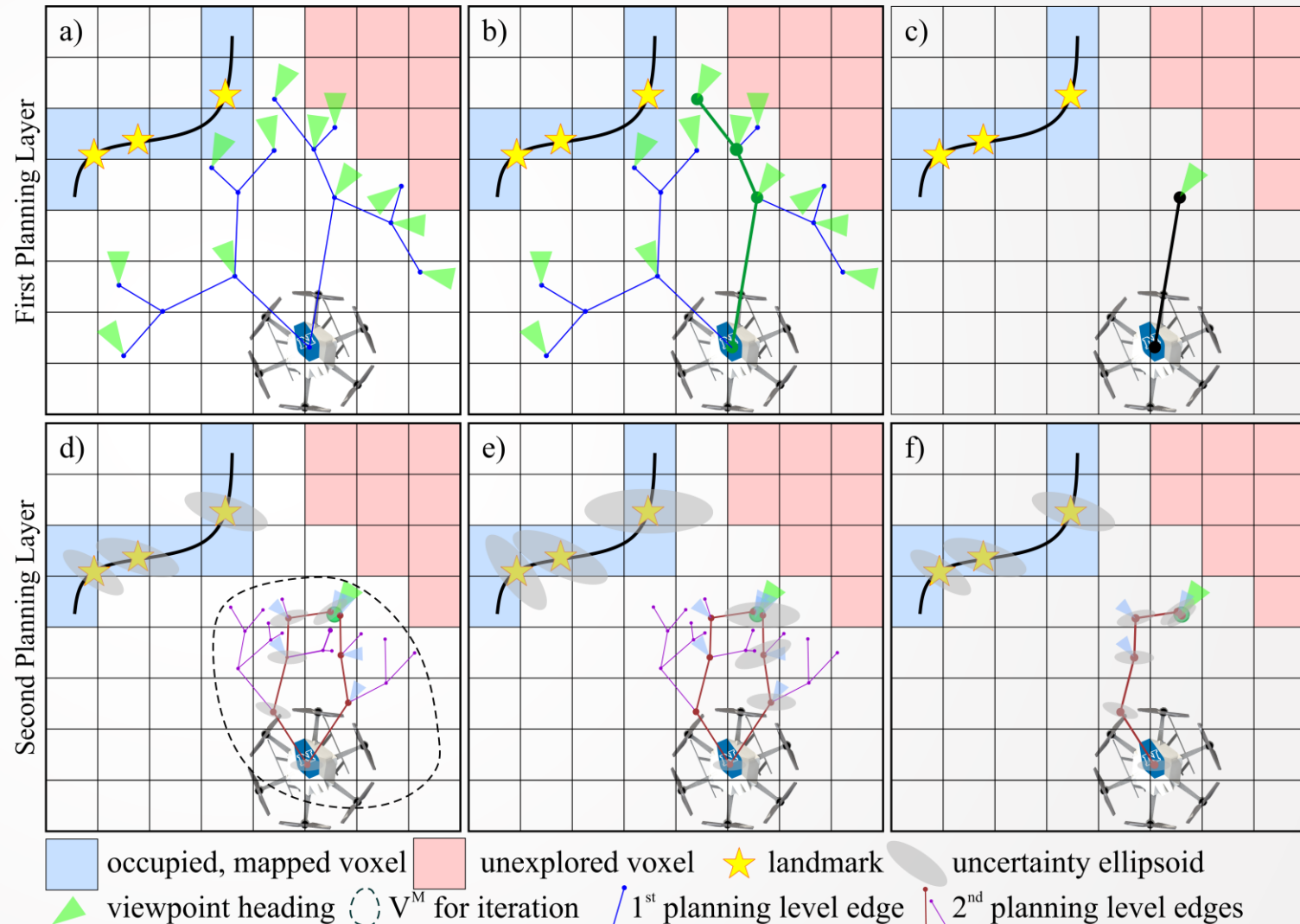
Exploration and Mapping Path Planning

- **Overall problem:** 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**.
- **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_{free}^E and V_{occ}^E when being executed, such that there does not exist any collision free configuration from which any piece of $V^E \setminus \{V_{free}^E, V_{occ}^E\}$ could be perceived.
- **Problem 2: Localizability-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.

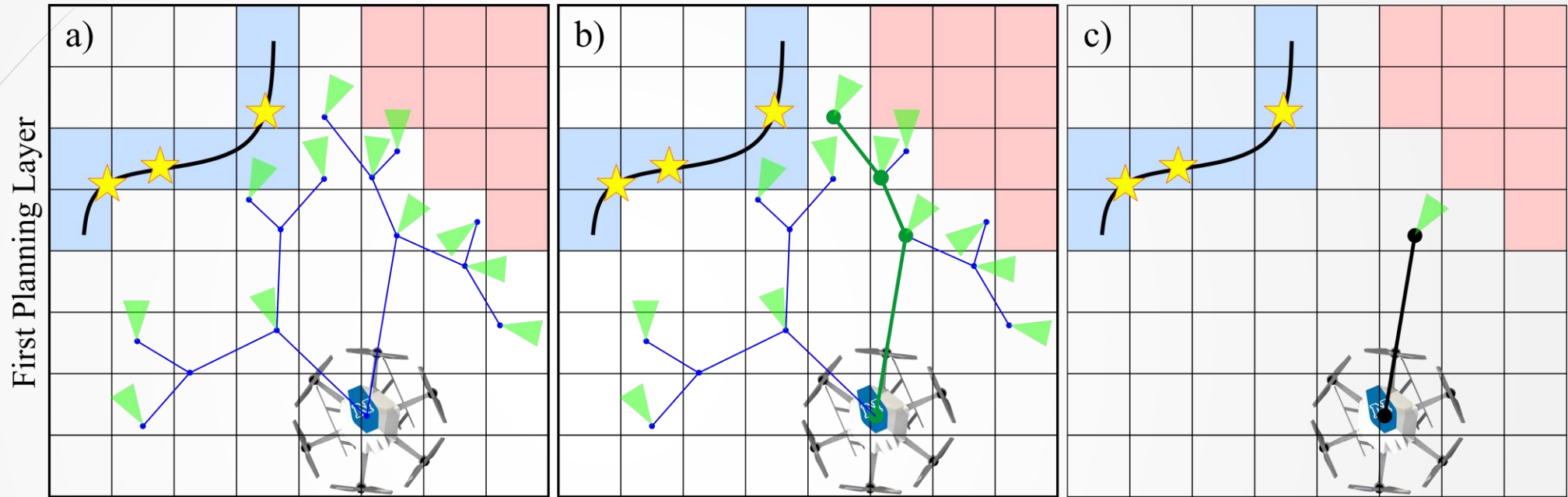
Exploration and Mapping Path Planning

Receding Horizon Exploration
and Mapping Planner
(rhemplanner)

Two-levels
Path Planning paradigm



Exploration step

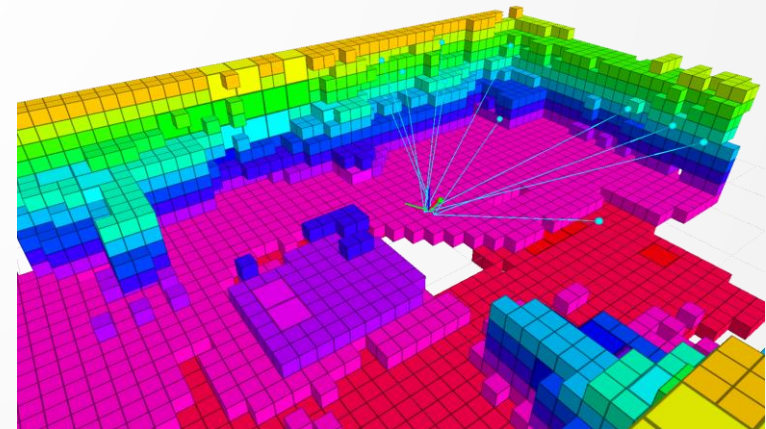
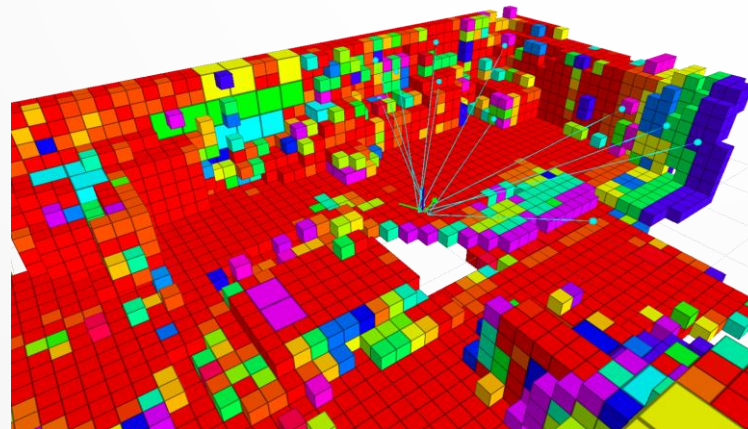


Exploration step

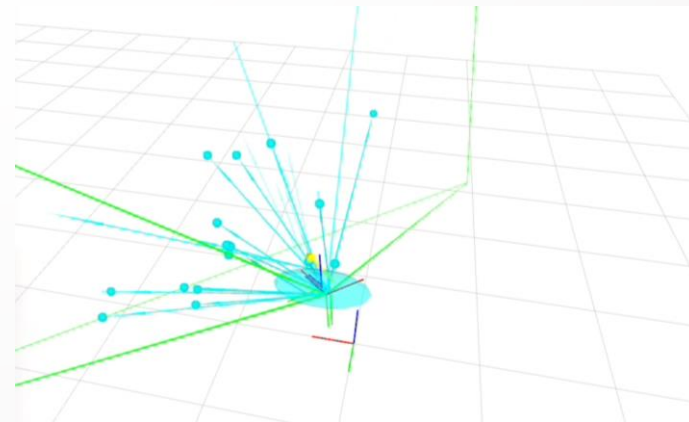
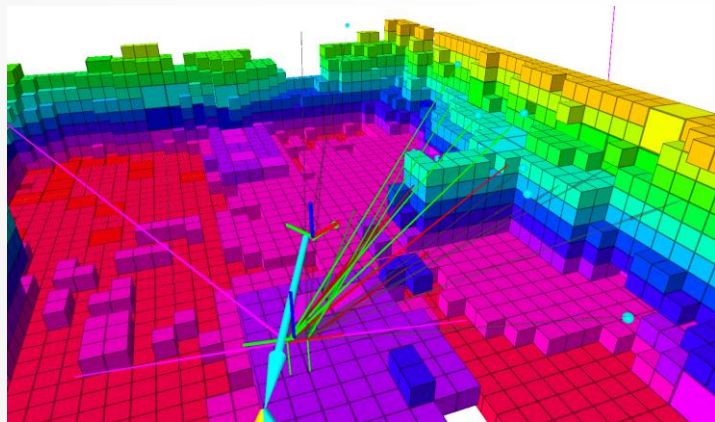
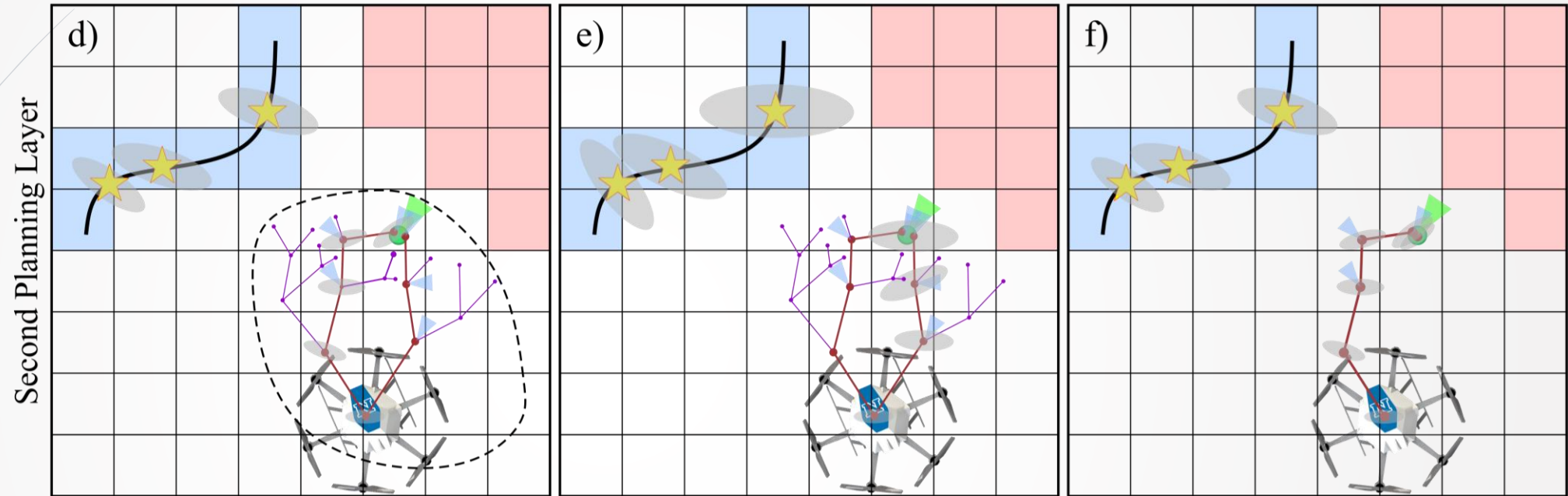
- **Exploration Gain** with **probabilistic re-observation**

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

- Aiming to maximize newly explored space and re-observe space with decreased confidence of being mapped as occupied.



Uncertainty-aware step



Uncertainty-aware step

- The robot performs **onboard localization and mapping**
 - For the case of our experiments it performs visual-inertial localization
 - The assumptions are:
 - Pose, features and their uncertainties are estimated
 - Dense, volumetric mapping takes place
- To get an estimate about its pose, it relies on tracking landmarks from its sensor systems. The system performs odometry in an EKF-fashion and the overall state of the filter is:

$$\mathbf{x} = \left[\overbrace{\begin{bmatrix} \mathbf{r} & \mathbf{q} & \mathbf{v} & \mathbf{b}_f & \mathbf{b}_\omega & \mathbf{c} & \mathbf{z} \end{bmatrix}}^{\text{pose, } l_p} \mid \underbrace{\begin{bmatrix} \mu_0, & \cdots & \mu_J & \rho_0 & \cdots & \rho_J \end{bmatrix}}_{\text{features states, } l_f} \right]^T$$

robot states, l_s features states, l_f

Uncertainty-aware step

- ➔ **Belief Propagation:** in order to identify the paths that minimize the robot uncertainty, a mechanism to propagate the robot belief about its pose and the tracked features has to be established.

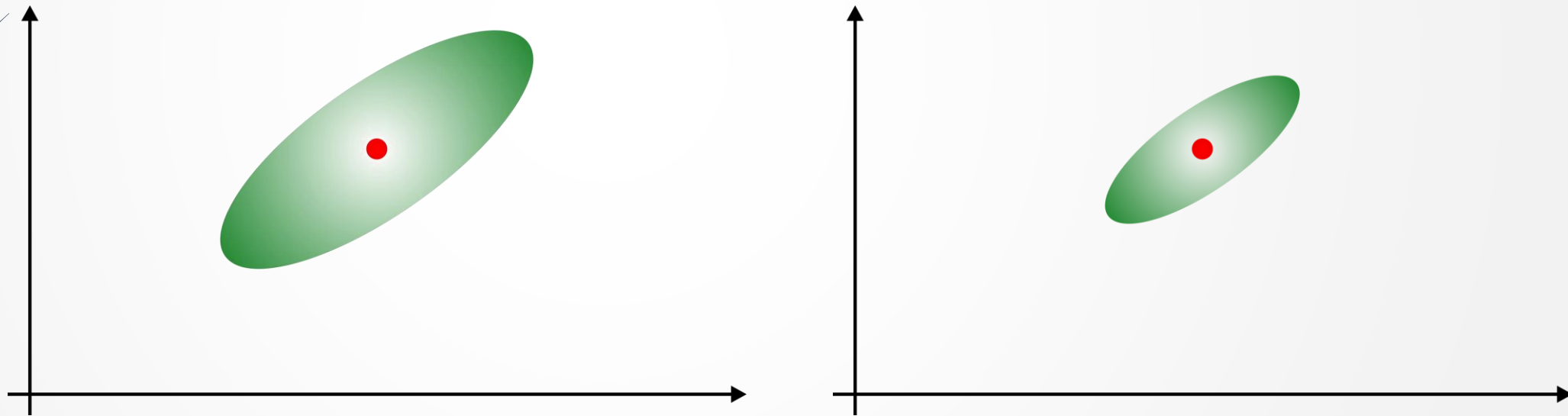
State Propagation Step - Equations (3)	Filter Update Step - Equations (4)
$\begin{aligned}\dot{\mathbf{r}} &= -\hat{\boldsymbol{\omega}}^\times \mathbf{r} + \mathbf{v} + \mathbf{w}_r \\ \dot{\mathbf{v}} &= -\hat{\boldsymbol{\omega}}^\times \mathbf{v} + \hat{\mathbf{f}} + \mathbf{q}^{-1}(\mathbf{g}) \\ \dot{\mathbf{q}} &= -\mathbf{q}(\hat{\boldsymbol{\omega}}) \\ \dot{\mathbf{b}}_f &= \mathbf{w}_{bf} \\ \dot{\mathbf{b}}_\omega &= \mathbf{w}_{b\omega} \\ \dot{\mathbf{c}} &= \mathbf{w}_c \\ \dot{\mathbf{z}} &= \mathbf{w}_z \\ \dot{\boldsymbol{\mu}}_j &= \mathbf{N}^T(\boldsymbol{\mu}_j)\hat{\boldsymbol{\omega}}_\mathcal{V} - \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \mathbf{N}^T(\boldsymbol{\mu}_j) \frac{\hat{\mathbf{v}}_\mathcal{V}}{d(\rho_j)} + \mathbf{w}_{\mu,j} \\ \dot{\rho}_j &= -\boldsymbol{\mu}_j^T \hat{\mathbf{v}}_\mathcal{V} / d'(\rho_j) + w_{\rho,j}\end{aligned}$	$\begin{aligned}\mathbf{y}_j &= \mathbf{b}_j(\boldsymbol{\pi}(\hat{\boldsymbol{\mu}}_j)) + \mathbf{n}_j \\ \mathbf{H}_j &= \mathbf{A}_j(\boldsymbol{\pi}(\hat{\boldsymbol{\mu}}_j)) \frac{d\boldsymbol{\pi}}{d\boldsymbol{\mu}}(\hat{\boldsymbol{\mu}}_j)\end{aligned}$ <p>By stacking the above terms for all visible features, standard EKF update step is directly performed to derive the new estimate of the robot belief for its state and the tracked features.</p>
<h3>Notation</h3> <p>$\times \rightarrow$ skew symmetric matrix of a vector, $\tilde{\mathbf{f}} \rightarrow$ proper acceleration measurement, $\tilde{\boldsymbol{\omega}} \rightarrow$ rotational rate measurement, $\hat{\mathbf{f}} \rightarrow$ biased corrected acceleration, $\hat{\boldsymbol{\omega}} \rightarrow$ bias corrected rotational rate, $\mathbf{N}^T(\boldsymbol{\mu}) \rightarrow$ projection of a 3D vector onto the 2D tangent space around the bearing vector, $\mathbf{g} \rightarrow$ gravity vector, $\mathbf{w}_\star \rightarrow$ white Gaussian noise processes, $\boldsymbol{\pi}(\boldsymbol{\mu}) \rightarrow$ pixel coordinates of a feature, $\mathbf{b}_i(\boldsymbol{\pi}(\hat{\boldsymbol{\mu}}_j)) \rightarrow$ a 2D linear constraint for the j^{th} feature which is predicted to be visible in the current frame with bearing vector $\hat{\boldsymbol{\mu}}_j$</p>	

Using Michael Bloesch, Sammy Omari, Marco Hutter, Roland Siegwart, "ROVIO: Robust Visual Inertial Odometry Using a Direct EKF-Based Approach", IROS 2015

Uncertainty-aware step

- **Uncertainty optimization:** to be able to derive which path minimizes the robot uncertainty about its pose and the tracked landmarks, a metric of how small the covariance ellipsoid is has to be defined.

- **What metric?**



Uncertainty-aware step

- **Uncertainty optimization:** to be able to derive which path minimizes the robot uncertainty about its pose and the tracked landmarks, a metric of how small the covariance ellipsoid is has to be defined.

- **D-optimality metric:**

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

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

Broadly: maximize the determinant of the information matrix $X'X$ of the design. This criterion results in maximizing the differential Shannon information content of the parameter estimates.

Exploration and Mapping Path Planning

First Planning Step

- ▶ $\xi_0 \leftarrow$ current vehicle configuration
- ▶ Initialize T^E with ξ_0
- ▶ $g_{best}^E \leftarrow 0$ // Set best exploration gain to zero
- ▶ $n_{best} \leftarrow n_0(\xi_0)$ // Set best exploration node to root
- ▶ $N_T^E \leftarrow$ Number of nodes in T^E
- ▶ **While** $N_T^E < N_{max}^E$ or $g_{best}^E == 0$ **do**
 - ▶ Incrementally build T^E by adding $n_{new}^E(\xi_{new}^E)$
 - ▶ $N_T^E \leftarrow N_T^E + 1$
 - ▶ **if** $\text{ExplorationGain}(n_{new}^E) > g_{best}^E$ **then**
 - ▶ $n_{new}^E \leftarrow n_{new}^E$
 - ▶ $g_{best}^E \leftarrow \text{ExplorationGain}(n_{new}^E)$
 - ▶ **if** $N_T^E > N_{TOT}^E$ **then**
 - ▶ Terminate planning
- ▶ $\sigma_{RH}^E, n_{RH}^E, \xi_{RH} \leftarrow \text{ExtractBestPathSegment}(n_{best})$
- ▶ $S_{\xi_{RH}} \leftarrow \text{LocalSet}(\xi_{RH})$

Exploration and Mapping Path Planning

Second Planning Step

- ▶ Propagate robot belief along σ_{RH}^E
- ▶ $a \leftarrow 1$ // number of admissible paths
- ▶ $g_a^M \leftarrow \text{BeliefGain}(\sigma_{RH}^E)$
- ▶ $g_{best}^M \leftarrow g_a^M$ // straight path belief gain
- ▶ $\sigma_{best}^M \leftarrow \sigma_{RH}^M$
- ▶ **while** $N_T^M < N_{max}^M$ or $V(T^M) \cap \emptyset S_{\xi_{RH}}$ **do**
 - ▶ Incrementally build T^M by adding $n_{new}^M(\xi_{new})$
 - ▶ Propagate robot belief from current to planned vertex
 - ▶ **if** $\xi_{new} \in S_{\xi_{RH}}$ **then**
 - ▶ Add new vertex n_{new}^M at ξ_{RH} and connect
 - ▶ $a \leftarrow a + 1$
 - ▶ $\sigma_a^M \leftarrow \text{ExtractBranch}(n_{new}^M)$
 - ▶ $g_a^M \leftarrow \text{BeliefGain}(\sigma_a^M)$
 - ▶ **if** $g_a^M < g_{best}^M$ **then**
 - ▶ $\sigma^M \leftarrow \sigma_a^M$
 - ▶ $g_{best}^M \leftarrow g_a^M$
- ▶ **return** σ^M

Flight Control System

- Model-based approach
- System identification
 - By identifying the parameters of a nonlinear differential equation $\dot{x} = f(x, u)$ representing the vehicle dynamics, a sufficiently accurate model is derived.
- Cascaded Flight Control:
 - **Model Predictive Control** strategies are employed for the position control of the vehicle
 - **Saturated fixed-gain loops** ensure fast and accurate tracking of the attitude references
- **Why MPC?**
 - Robustly accurate response
 - Respects system constraints

$$J_0(x_0, U, X_{ref}, U_{ref}) = \sum_{k=0}^{N-1} (x_k - x_{ref,k})^T Q_x (x_k - x_{ref,k}) + (u_k - u_{ref,k})^T R_u (u_k - u_{ref,k}) + (u_k - u_{k-1})^T R_\Delta (u_k - u_{k-1}) + (x_N - x_{ref,N})^T P (x_N - x_{ref,N}),$$

Fast Nonlinear Model Predictive Control for Multicopter Attitude Tracking on S0(3)

Mina Kamel, Kostas Alexis, Markus Achtelik and Roland Siegwart

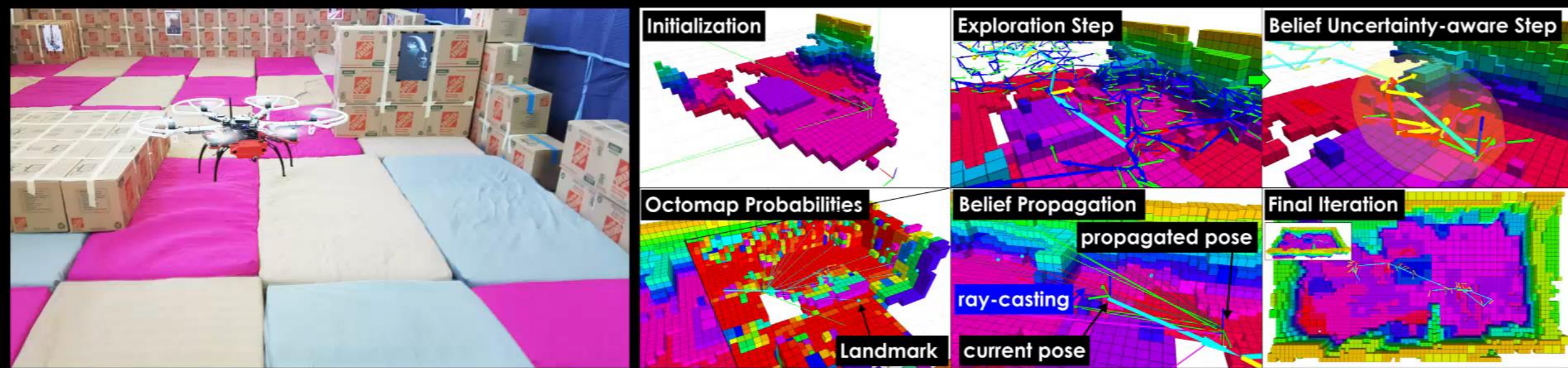


Position tracking without one propeller



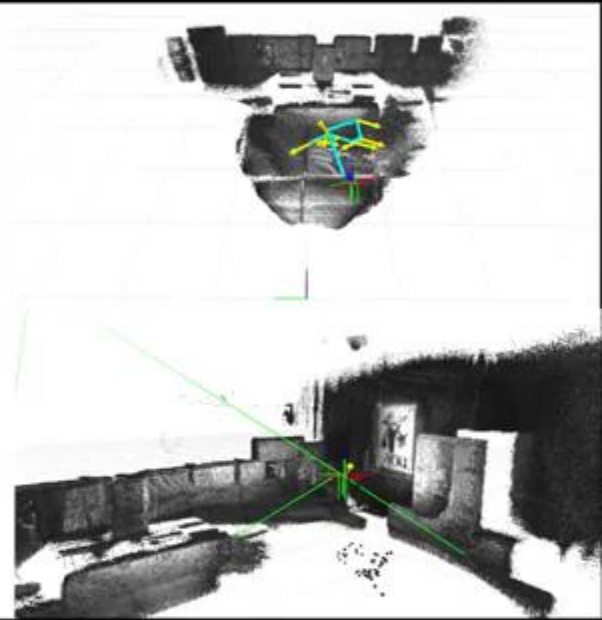
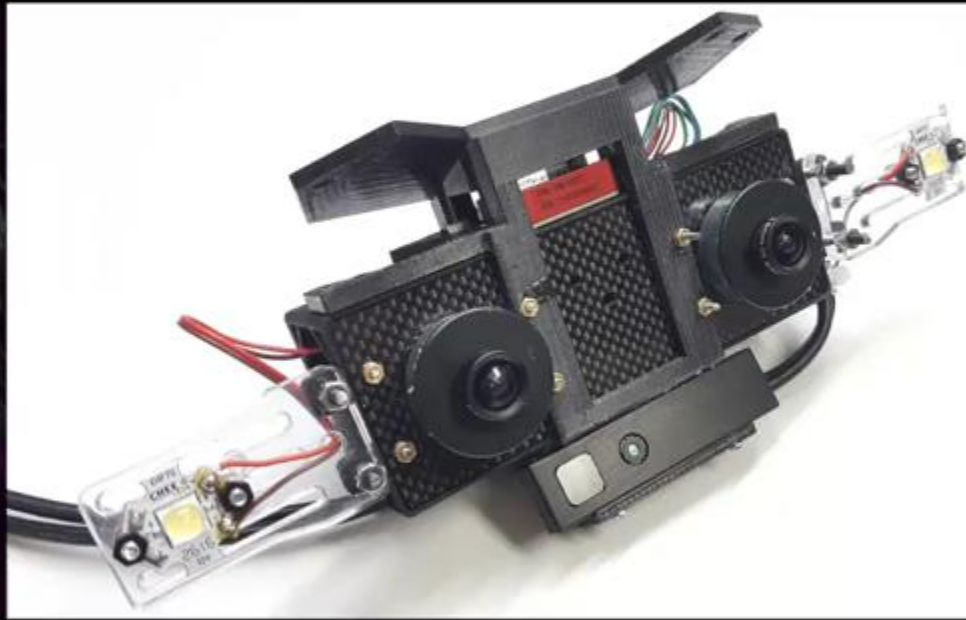
Uncertainty-aware Receding Horizon Exploration and Mapping using Aerial Robots

Christos Papachristos, Shehryar Khattak, Kostas Alexis



A Multi-Modal Mapping Unit for Autonomous Robotic Navigation and Exploration in Visually-degraded Environments

Frank Mascarich, Christos Papachristos, Kostas Alexis

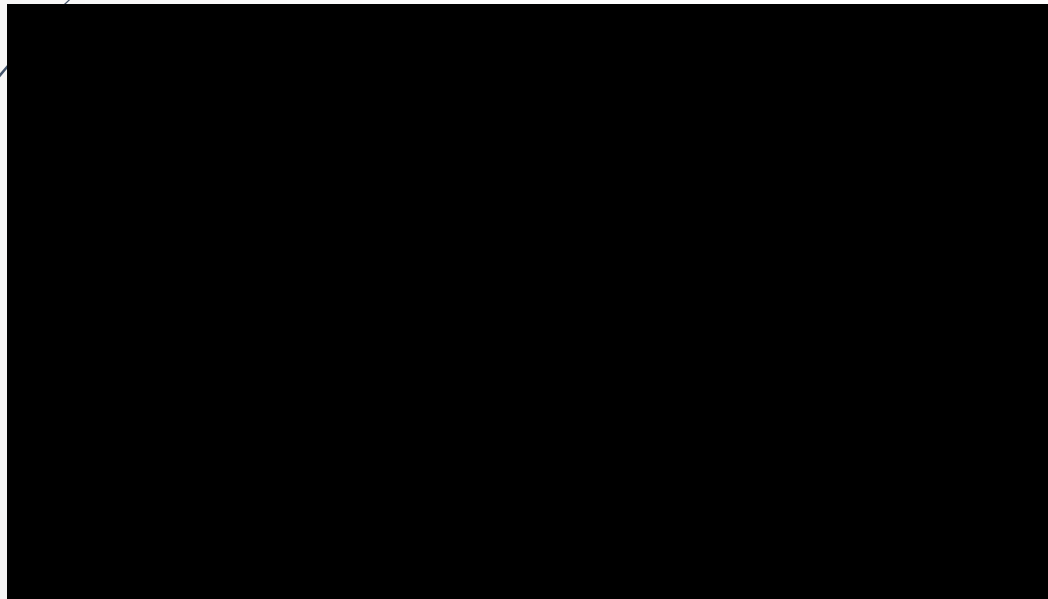


This material is based upon work supported by the Department of Energy under Award Number [DE-EM0004478]



Multiple Aerial Robotic Configurations

- Different aerial robot configurations are designed to address the specific challenges of different applications and environments.
- Our lab develops multirotor and fixed-wing vehicles while carries experiences from **Solar-powered UAV** design and **convertible systems** (work at ETH Zurich)



Robots on the Ground

- ▶ Planned robotic research aims to address challenges related to autonomous transportation systems and legged robotic autonomy.
- ▶ Extension of our closed Perception-Planning-Control research approach



New Initiative: Intelligent Mobility

- Driverless cars are “indicative examples” of how robots can become ubiquitous.
- But for such robots to be able and be trusted to operate autonomously in our cities, the challenges in perception, planning, control and multi-robot collaboration have to be robustly addressed.
- The Intelligent Mobility project is a university initiative that reaches to multiple collaborations locally, nationally and internationally.
- Specifics:
 - **Goal:** Enhance the safety and systematicity of public transportation systems through autonomous technologies. Pave the way towards autonomous public transportation.
 - **Testing:** Sierra Spirit Route of the RTC (vehicle performing its normal operation)



Marine Robotics

- ▶ Maritime robotics have an exciting set of possible applications.
 - ▶ Among others related to the protection of our water ecosystems.
- ▶ In collaboration with the department of biology we investigate the development of a robotic boat that performs automated algae detection and mapping for Lake Tahoe.
- ▶ Combined perception system:
 - ▶ Above water: Large baseline stereo, IMU, GPS
 - ▶ Underwater: Camera and illumination system to detect algae based on its specific spectrum response.





Autonomous Marine Robotics to Detect Change in Freshwater Ecosystems Test #3

Autonomous Robots Lab
Nevada Advanced Autonomous Systems Innovation Center



Robots in the Wild

- ▶ Experiments in the laboratory is how robotic technology gets verified and improved. But the natural environment of robots is out in the wild.
- ▶ One of the most fundamental directions of our work is related to field evaluation. **Field robotics** research is the key for systems to be optimized and for the society to see the benefits and abilities of robotics technology.



Exploration and Mapping in Visually-degraded Environments

Preliminary results

C. Papachristos, S. Khattak, F. Mascarich, K. Alexis

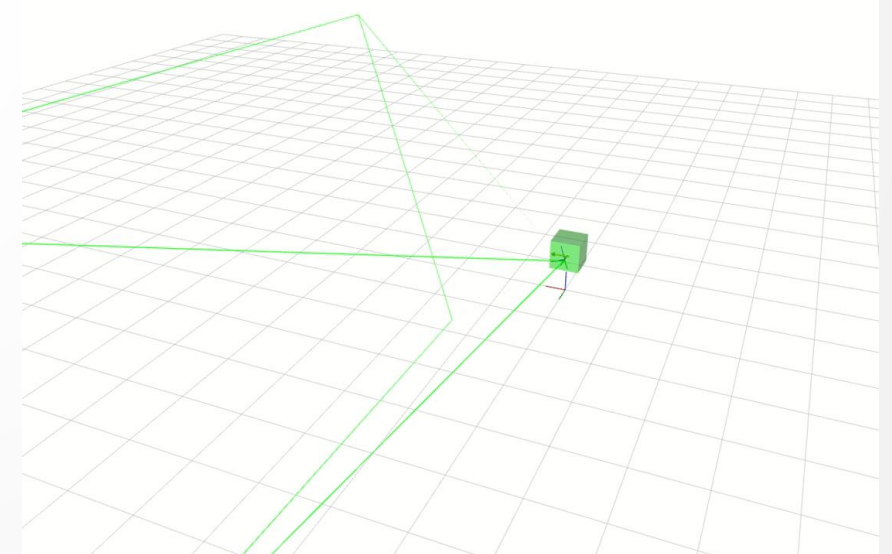
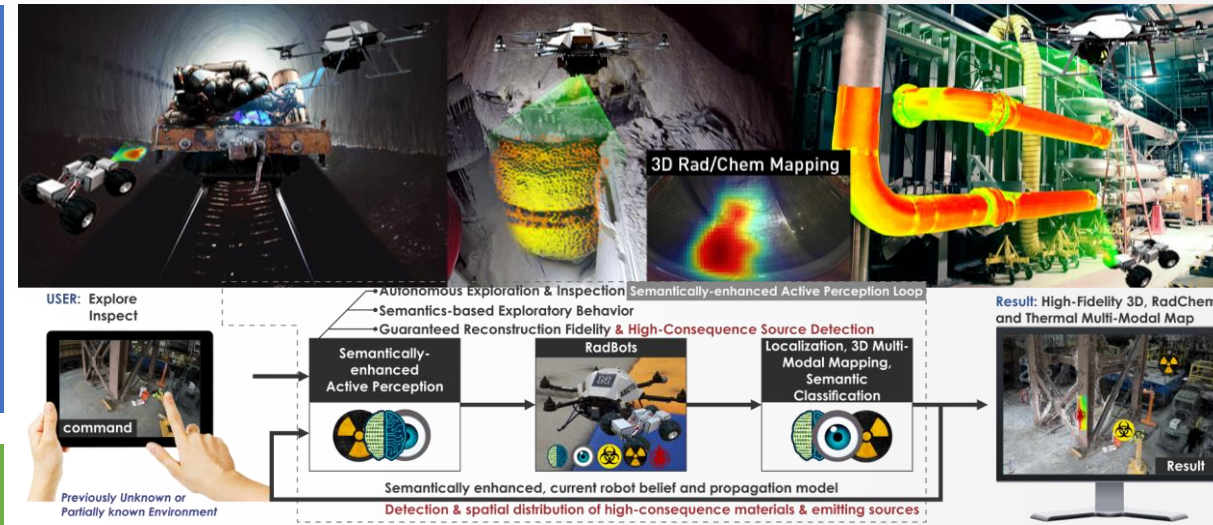


Multi-modal characterization of Nuclear Sites

- Combined roving and flying robots to characterize DOE-EM facilities.
- Identification and semantic classification of tanks, pipes, and other important structures to intelligently focus the robot exploration and inspection tasks.
- Radiation, chemical, and heat spatial maps are fused with 3D models of the environment

- Integrated planning and multi-modal perception for comprehensive mapping of nuclear facilities.
- Augmented exploration-planning to account for the radiation, chemical, and heat estimates.
- Coordination of aerial and ground robots to maximize the capabilities of both platforms.
- Demonstration in DOE-EM relevant, nuclear analog facilities towards advanced technology readiness.
- Course curriculum development and K-16 outreach.

- Collaboration with nuclear engineering pioneers (Taylor Wilson)





Educational Activities

Educational Activities

CS491/691: Introduction to Aerial Robotics

- Aerial robot dynamics
- State estimation
- Flight control
- Motion planning
- Partially project-based

CS491/691: Autonomous Mobile Robot Design

- Robot dynamics & Kinematics
- State estimation
- Simultaneous Localization and Mapping
- Robot control
- Path planning
- Fully project-based

ENGR471: Flight Coordinator Course

- Education on the operational aspects of Unmanned Aerial Vehicles.
- Introduction to basic aerodynamics, communication systems and more.
- In collaboration with Insitu

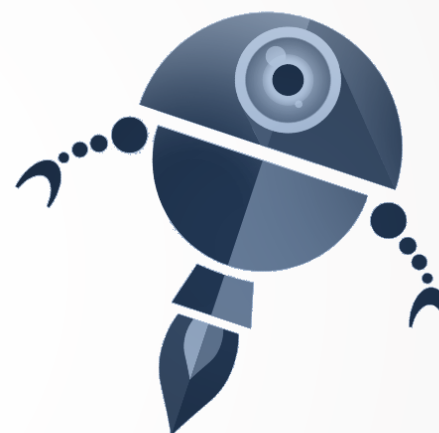


Robotics Short Seminar series

- Topic-specific talks with invited colleagues from the UNR, other academic institutions or the industry.

Outreach

- Supporting the UNR UAS summer campus
- Robot projects for school students and community colleges
- Online examples and videos



AUTONOMOUS ROBOTS ARENA

The Autonomous Robots Arena

- 10 Vicon Vantage V8 Motion Capture System cameras and the Tracker Software.
- 15x7x5m theoretical motion-capture enabled volume. Sub-mm and Sub-degree accuracy.
- 14x6.5x4m actual robust operation for 2+ more tracking and gap within the volume.
- A main computer running the official software. A powerful computer running ROS to support easy robot integration.
- Mock-ups installed inside for challenging experiments (more than 300 boxes to create different geometric forms).
- Three separate networking options.
- Visual-light cameras also and synchronized



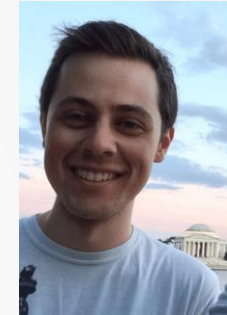
Open Source contributions



➤ Open Source Code:

- Structural Inspection Planner:
 - <https://github.com/ethz-asl/StructuralInspectionPlanner>
- Next-Best-View Planner:
 - <https://github.com/ethz-asl/nbvplanner>
- Receding Horizon Exploration and Mapping Planner:
 - <https://github.com/unr-arl/rhemplanner>
- Robust Model Predictive Control
 - https://github.com/unr-arl/rmpc_mav
- Dubins Airplane Solver
 - <https://github.com/unr-arl/DubinsAirplane>
- Motion Analysis Cortex ROS Bridge
 - https://github.com/unr-arl/cortex_ros_bridge

The team



- Established at January 2016
- **Current Team:** 1 Head, 1 Senior Postdoctoral Researcher, 3 PhD Candidates, 1 Graduate Research Assistant, 2 Undergraduate Researchers
- **From summer 2017:** 1 more Senior Postdoctoral Researcher and 1 more PhD Candidate



Thank you!

Please ask your question!