Aerial Robotics for Exploration of Subterranean Environments

C. Papachristos, Frank Mascarich, S. Khattak, T. Dang, Kostas Alexis

Autonomous Robots Lab, University of Nevada, Reno


LiDAR-based mapping in underground mine drift
Intro View

Subterranean Robotics Operations

- Subterranean environments impose extreme challenges for robotic operation – among others:
  - Visually-degraded, often dark, and dust/fog/smoke-filled GPS-denied environments.
  - Challenging terrain, complex geometry and frequently very narrow and confined settings.
  - Limited communication capacity between the robotic team and between robots and the human operator(s).
  - Very limited training data for very diverse environments.

Subterranean Robotics Operations

- Subterranean environments correspond to important operational domains for robots – e.g.:
  - For industry-related applications such as underground mine inspection, vehicle localization and SAR.
  - For urban infrastructure monitoring such as the inspection of sewers and subway stations.
  - For security inspection of critical infrastructure such as the case of the nuclear complex.
  - For security surveillance operations in the most challenging environments.

Subterranean Robotics Operations

- Autonomous, robust and long-term robotics operation in underground settings requires novel research in systems and methods – among others for:
  - Robotic perception in visually- and broadly sensing degraded environments.
    - *Example:* an underground coal mine with a fire accident.
  - Robotic exploration and informative path planning for accessing and mapping subterranean spaces.
    - *Example:* exploring a cave or inspecting city sewers.
  - Collision-resilient robotic navigation.
    - *Example:* an aerial robot going through a narrow manhole.
  - Detection of objects of interest subject to lack of training data.
    - *Example:* what objects is an anomaly inside a cave?

Subterranean Robotics Operations

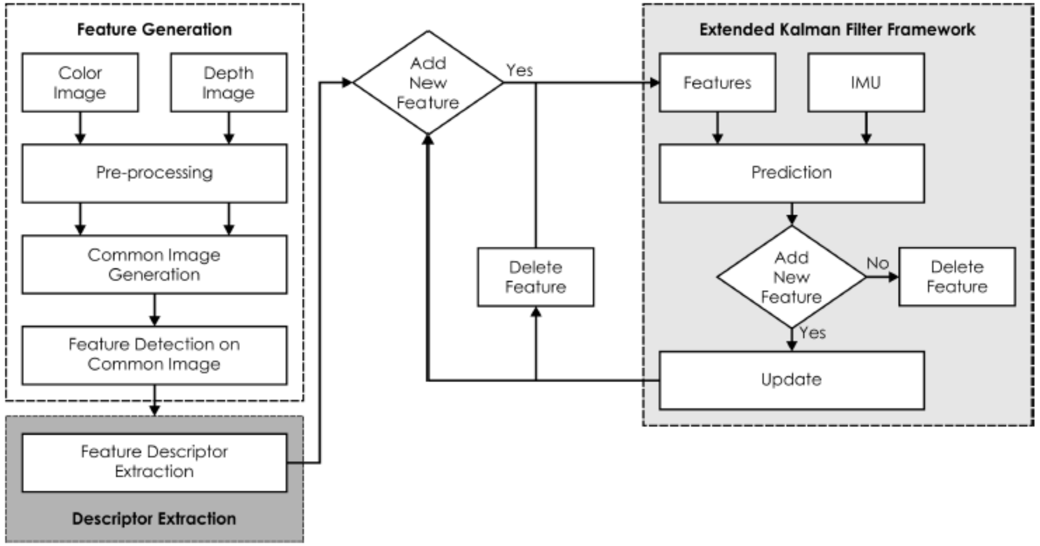
- In response to these challenges, our research focuses on the following algorithmic and technological contributions:
  - Multi-modal robotic perception for robust localization and mapping in GPS-denied visually-degraded underground environments.
  - Informative path planning for exploration such that it simultaneously accounts for the vehicle localization uncertainty and the visual saliency of objects.
  - Physical interaction-enabled collision-tolerant flight.
  - Saliency-driven proto-object detection and one-class classification given only "positive" data.
  - Field deployments enabling specific analysis and problem-driven research.

Multi-Modal Robotic Perception

- Multi-modal sensor fusion for subterranean robots:
  - Selected modalities:
    - Visible-light cameras
    - Thermal vision
    - LiDAR sensors
    - IMU cues

Two test robots:
1. Visual/Thermal-Inertial
2. LiDAR/Visual/Inertial

  - Multi-modal features across camera and depth range data. Common detectors & descriptors.
  - Loose fusion between visual and thermal camera data (tight fusion to be investigated).



Note: State-of-the-art methods of the community such as ROVIO and LOAM are part of the tests also.

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Evaluation in low-light environment with subsets of it lacking visual features but maintaining depth information.
Visual: ORB
Depth: Enhanced BRAND
merged

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Thermal-Inertial Localization for Autonomous Navigation of Aerial Robots through Obscurants

Christos Papachristos, Kostas Alexis

This material is based upon work related to the Mine Inspection Robotics project sponsored by the Nevada Knowledge Fund administered by the Governor's Office of Economic Development.

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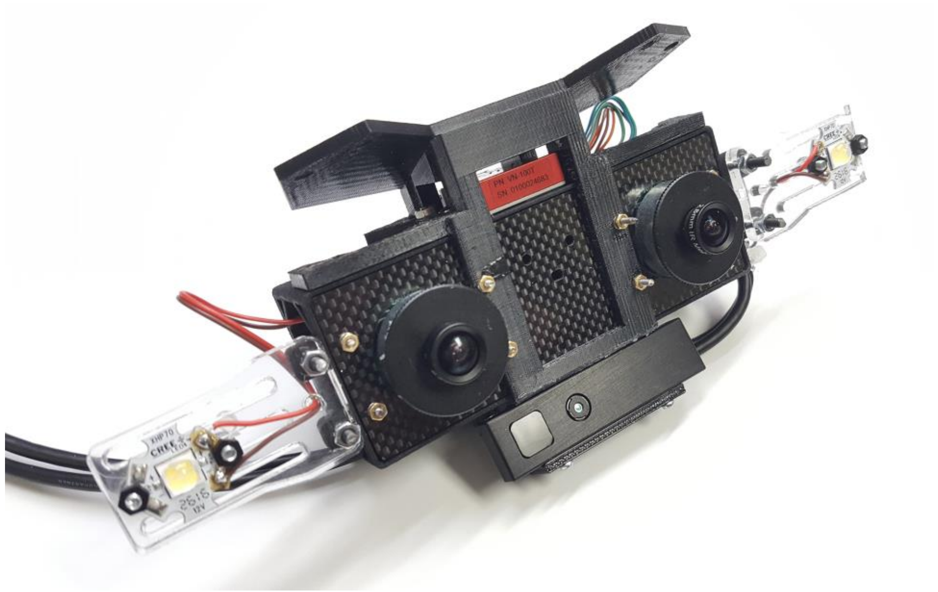
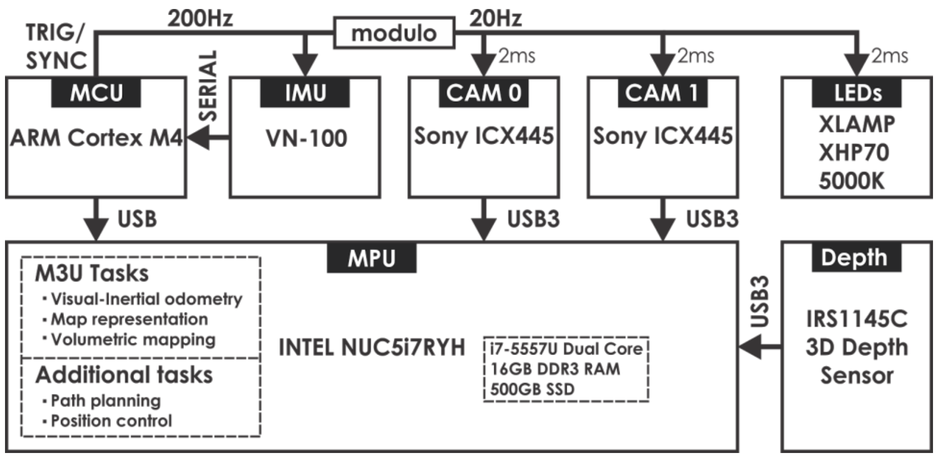
Multi-Modal Robotic Perception

- **Previous work also included the use of shutter-synchronized LEDs**
  - Stereo global shutter cameras with shutter opening synchronized with flashing LEDs.
  - IMU synchronized with vision (at 10x the rate)
  - Time-of-flight 3D Depth Sensing (software Synchronized)
  - Thermal Vision





Autonomous Aerial Robotic Exploration and Mapping of a Railroad Tunnel in Degraded Visual Conditions

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

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

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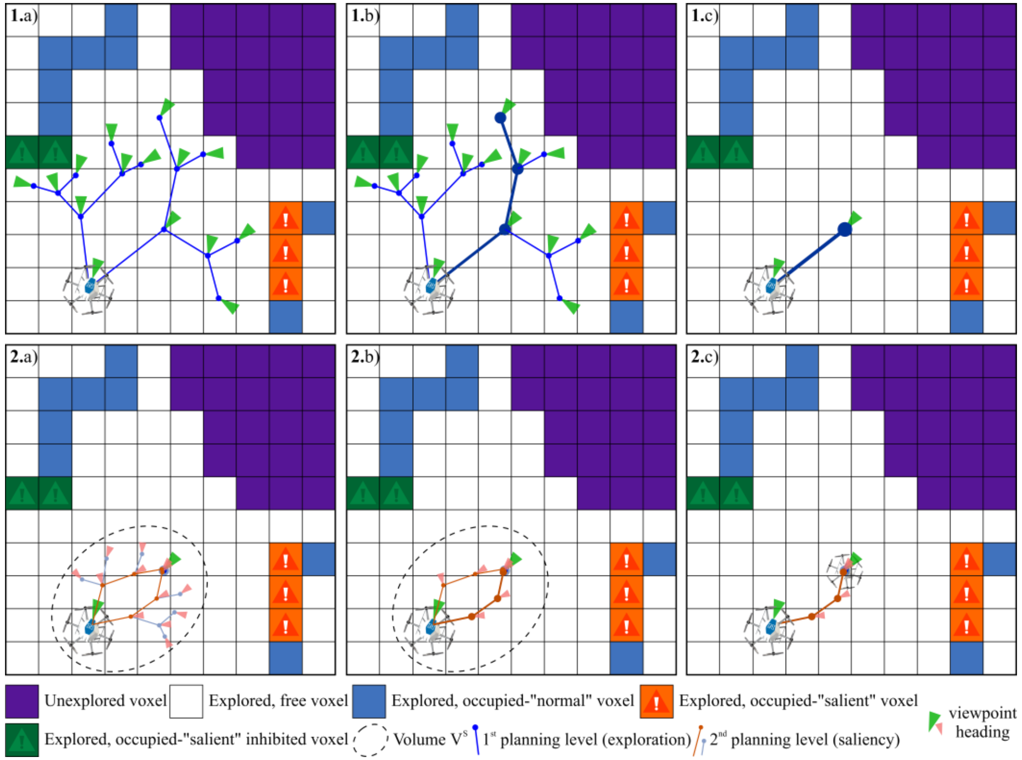
Informative Path Planning

- Informative path planning for subterranean exploration:
  - Planning objectives
    - Explore unknown areas
    - Account for uncertainty
    - Account for visual saliency

  Nested multi-step optimization
  1. Exploration
  2. Sub-objectives
  - Accounting for localization uncertainty is critical for long-term robotic deployment in visually-degraded environments.
  - Accounting for proto-objects detected through visual saliency approaches allows for intelligent information gathering in areas for which we lack training data.

Note: Most of these algorithms are open-sourced already from our group.



Informative Path Planning

- **Problem 1:**
  - Explore an unknown but bounded volume in Visually-degraded Conditions and derive a complete 3D model of it.

- **Problem 2:**
  - As the localization uncertainty depends on the viewpoints selected, the order that they are visited, and the motion patterns employed, ensure minimized localization uncertainty to ensure robust consistent mapping.

- **Problem 3:**
  - Account for visual saliency – visual context-aware exploration that focuses on objects that "pop out" and goes rapidly through self-similar environments.
  - Develop robot curiosity by detecting information gaps between perceptual stimuli and prior experiences. Self-supervised online learning based on learning progress.

Informative Path Planning

- Receding Horizon Exploration and Mapping Planner **(rhemplanner)**
- **Problem 1:**
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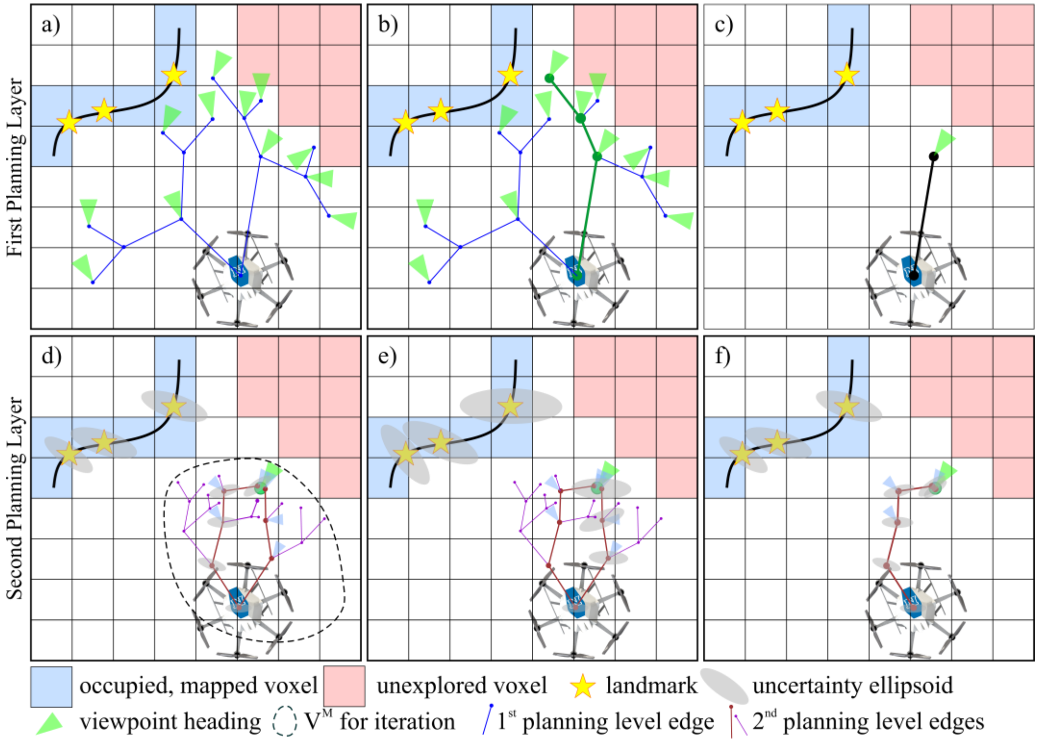
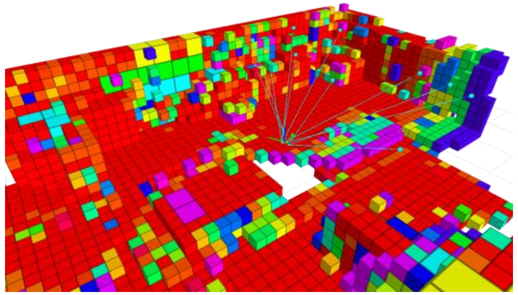
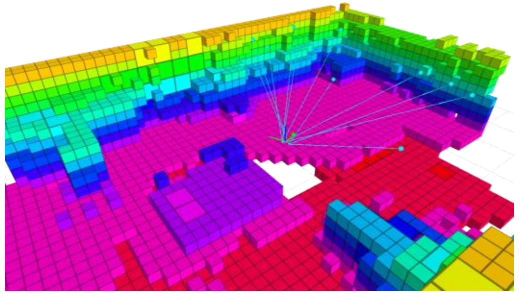


Informative Path Planning

- Receding Horizon Exploration and Mapping Planner **(`rhemplanner`)**
- **Exploration Gain**

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





- **Uncertainty Minimization**

$$\mathbf{x} = [\underbrace{\overbrace{\mathbf{r}\ \mathbf{q}}^{\text{pose},\ l_p}\ \boldsymbol{\upsilon}\ \mathbf{b}_f\ \mathbf{b}_\omega\ \mathbf{c}\ \mathbf{z}}_{\text{robot states},\ l_s} \mid \underbrace{\boldsymbol{\mu}_0, \cdots \boldsymbol{\mu}_J\ \rho_0 \cdots \rho_J}_{\text{features states},\ l_f}]^T$$

  - **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.

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

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

Informative Path Planning

- Visual Saliency-aware Exploration Planner **(`vseplanner`)**
- **Problem 1:**
  - Explore an unknown but bounded volume and derive a complete 3D model of it.
- **Problem 3:**
  - Account for visual saliency – visual context-aware exploration that focuses on objects that "pop out" and goes rapidly through self-similar environments.
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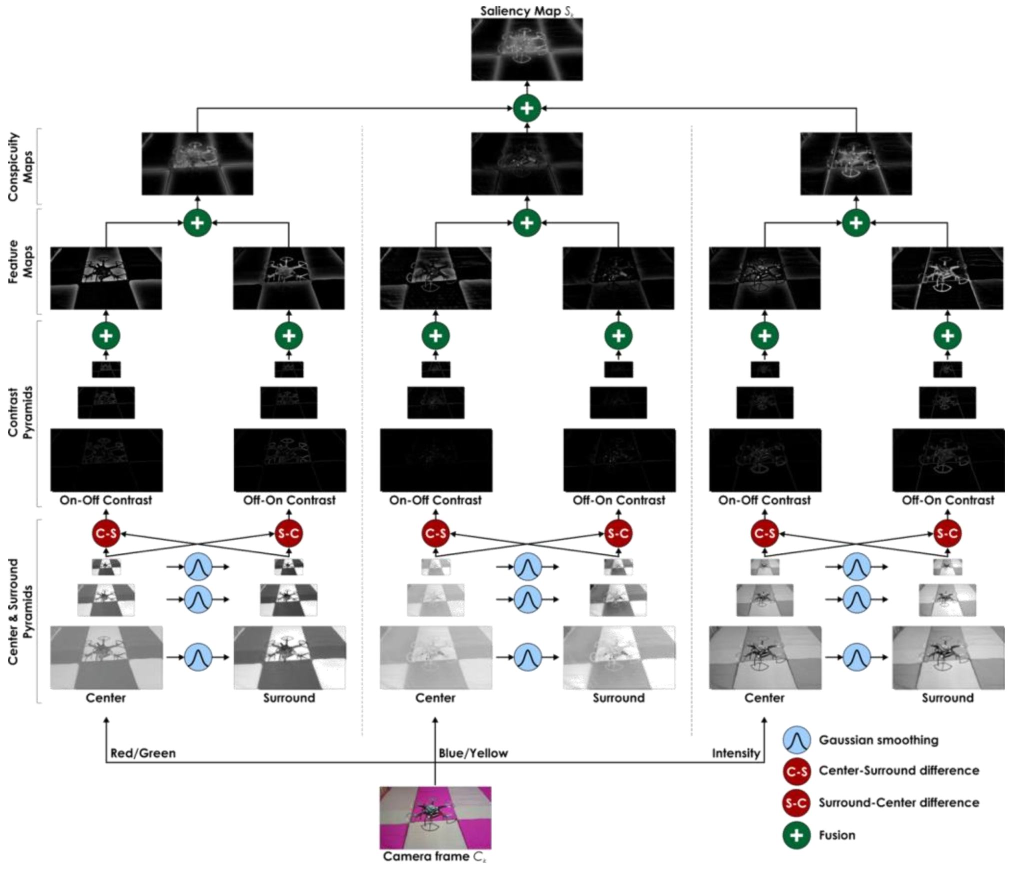
Informative Path Planning

- **Visual Saliency Model**
  - Saliency is the distinct subjective perceptual quality of certain objects and entities that makes them stand out from their neighbors and immediately attract our attention.



Frintrop, Simone, Thomas Werner, and German Martin Garcia. "Traditional saliency reloaded: A good old model in new shape." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2015.

Informative Path Planning

- **Saliency-encoded Occupancy Map**
  - **Five type of voxels**
    - Unknown, Explored-free, Explored-normal, Explored-salient, Explorent-salient-inhibited
  - **Saliency Map projection on Map**

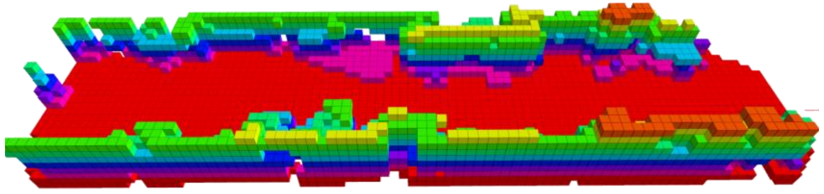
$$S_m^{\text{proj}} = \frac{1}{N} \sum_{[u,v] \in \text{proj}_{\mathcal{S}_\ell}^m} \mathcal{S}_\ell(u,v)$$

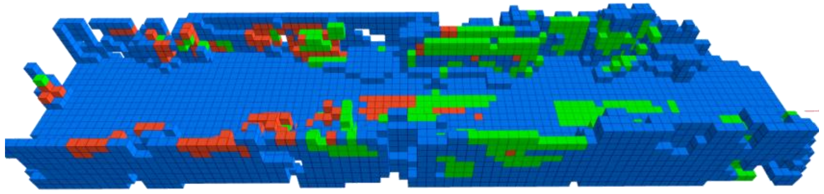
  - **Fusing multiple views for 3D saliency octomaps**

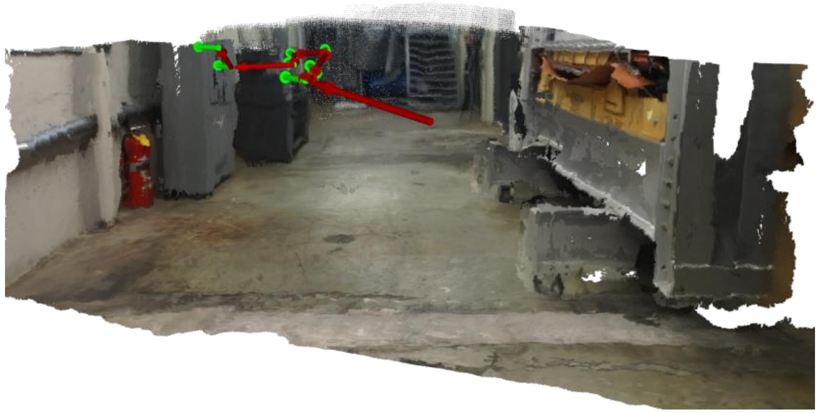
$$S_m^\ell = S_m^{\ell-1} + \gamma(S_m^{\text{proj}} - S_m^{\ell-1})$$

  - **Inhibition of Return in Occupancy Maps**
    - Enables attention-shift

$$S_m^{\ell-1} \leftarrow S_m^{\ell-1} e^{-\beta \Delta T}, \ \Delta T = t_\ell - t_{\ell-1}$$

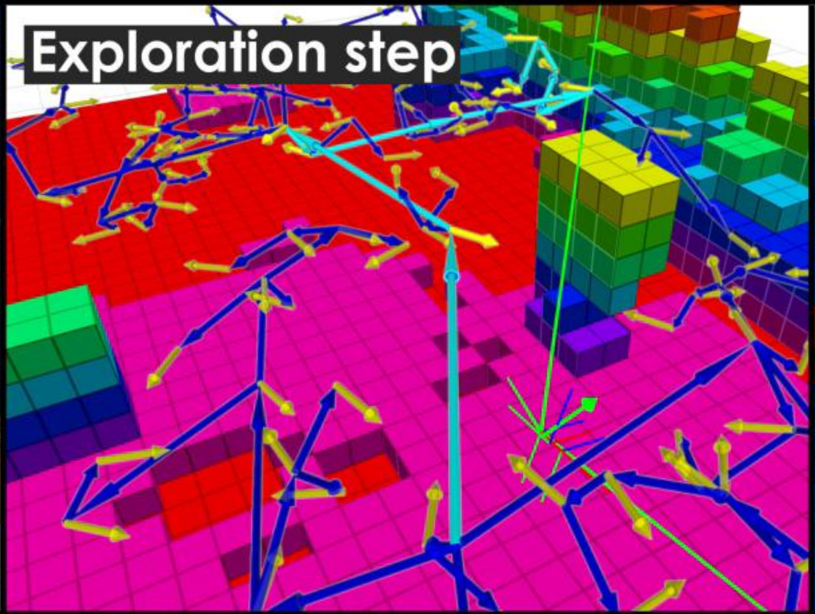


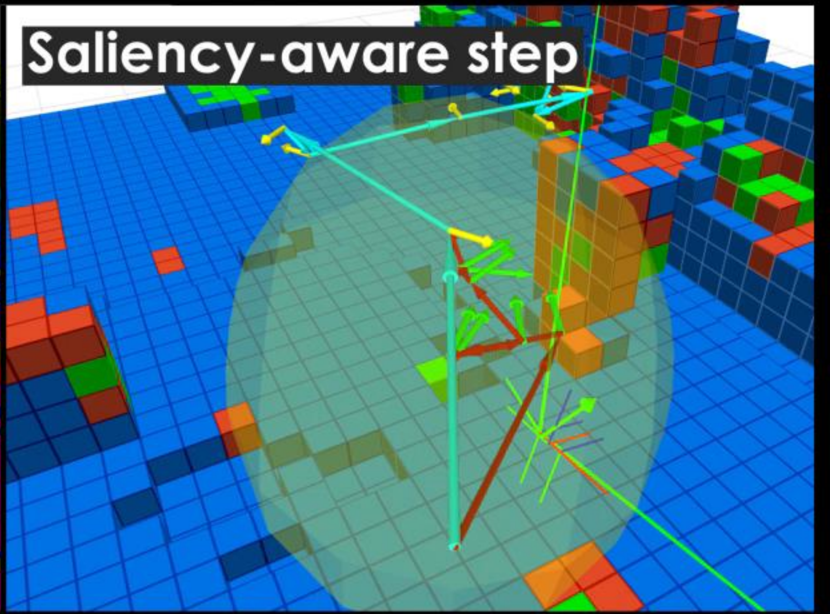




Visual Saliency-aware Receding Horizon Autonomous Exploration with Application to Aerial Robotics

Tung Dang, Christos Papachristos, Kostas Alexis





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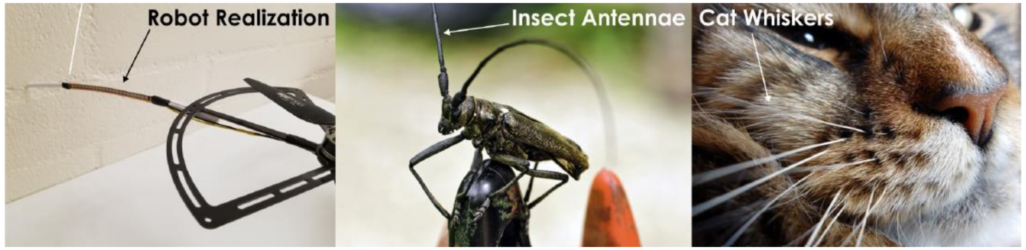
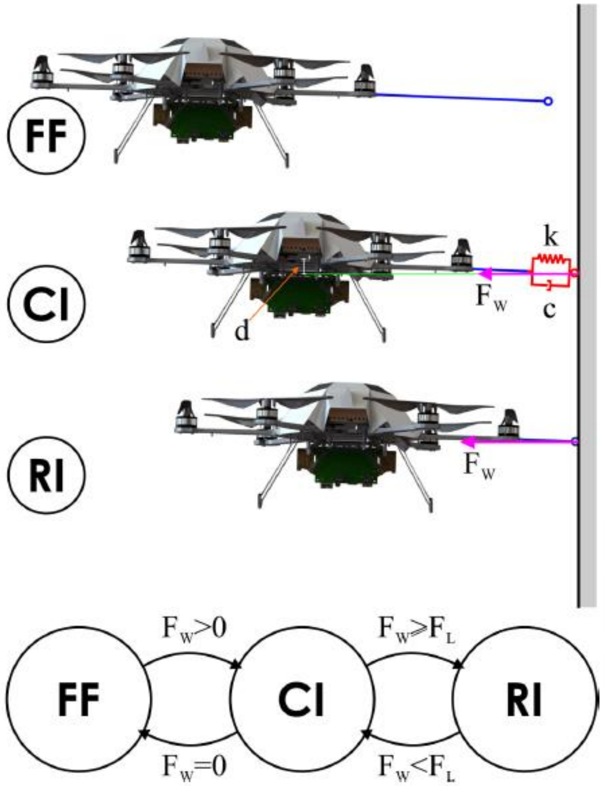
Physical Interaction-based Collision tolerance

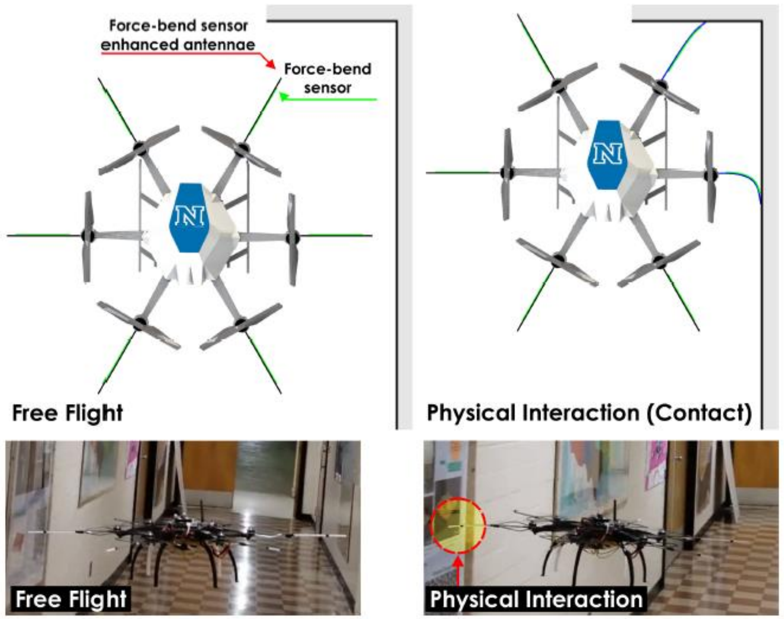
- Collision may be unavoidable if the robot access extremely narrow environments and some localization uncertainty cannot be eliminated.
- **Instead of assuming perfect avoidance of collision, an alternative would be to exploit them.**
- Enhance aerial robots with force/bend sensing antennae around their structure and deployment of interaction feedback-based control.
- **Provide a mechanism of resilience subject to pose and map estimation failure.**



Physical Interaction-based Collision tolerance

- Three modes of operation/hybrid system formulation:
  - Free-Flight (FF)
  - Compliant Interaction (CI)
  - Rigid Interaction (RI)
- Control law for collision-tolerance is purely reactive to minimize or eliminate interaction.
  - Future investigation will focus on wall-following and surface mapping through touch.





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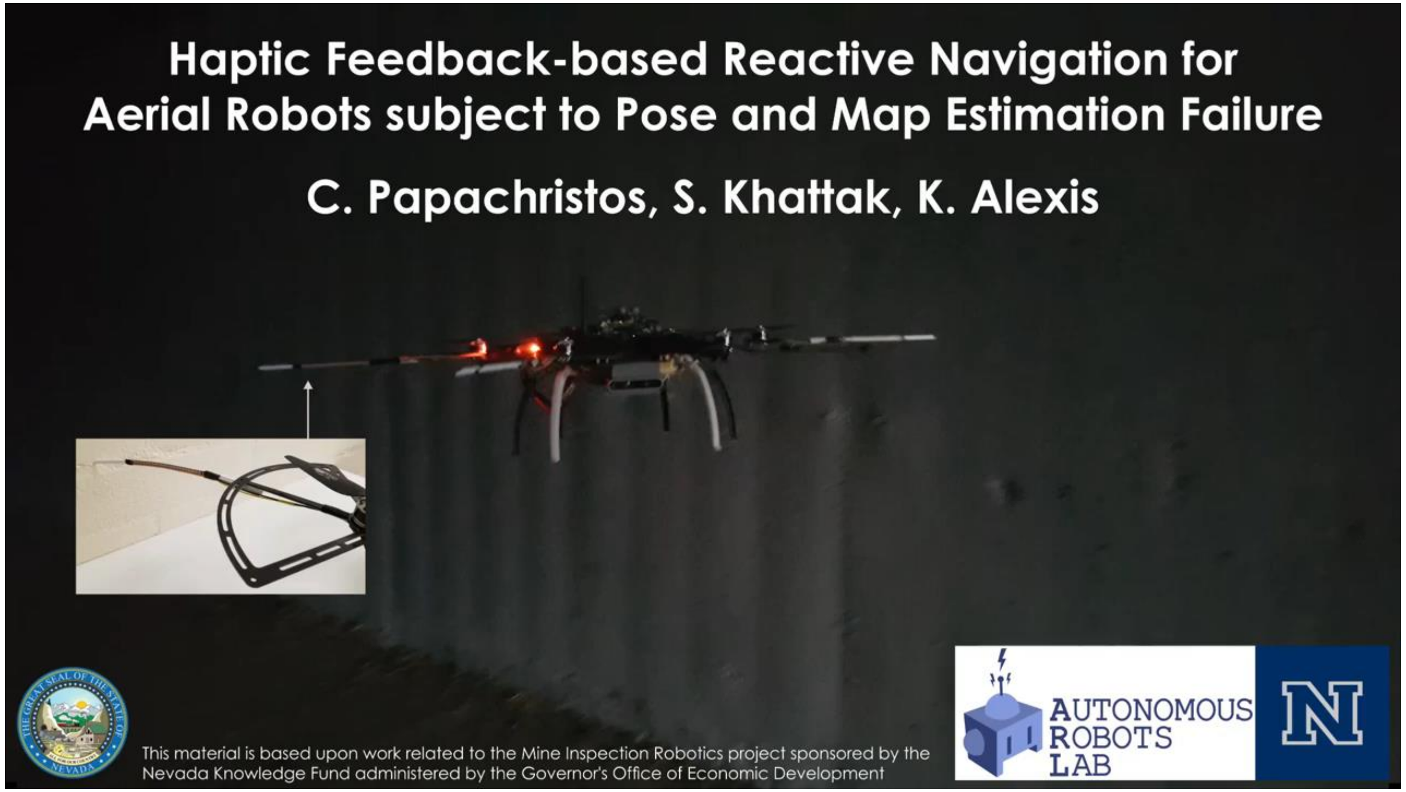
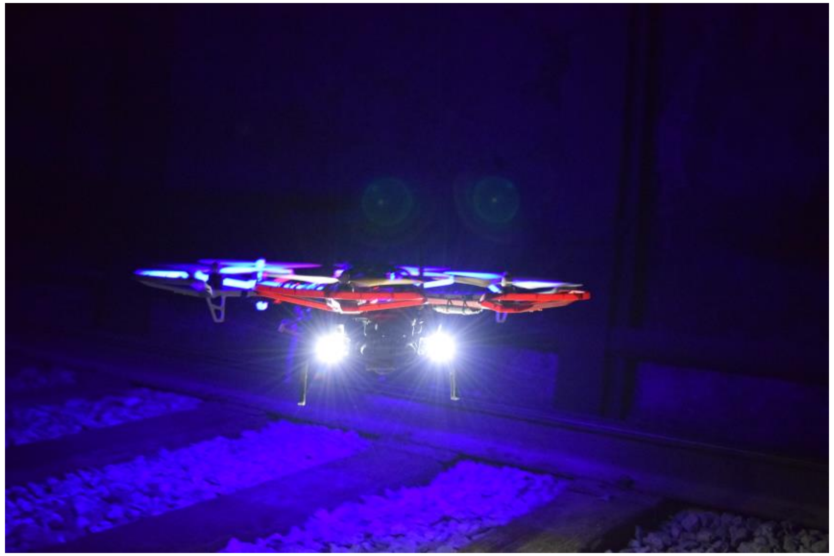
- Control law for collision-tolerance is purely reactive to minimize or eliminate interaction.
    - Future investigation will focus on wall-following and surface mapping through touch.
- **Method verified onboard a robot that was only left with IMU, barometric and force/bend sensing – no full pose/map estimation.**



Field Deployments

- The aforementioned research was tested and verified in different environments of interest, including:
  - Underground metal mines
  - Railroad tunnels in Virginia City, Nevada [**shown**]
  - Urban tunnels in Reno, Nevada
  - Smoke-filled industrial environments at the university [**shown**]



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Field Deployment of Autonomous Aerial Robots in Underground Mines

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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/rhem_planner
  - Visual Saliency-aware Exploration Planning
    - https://github.com/unr-arl/vseplanner


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Thank you!
Please ask your question!
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