# Autonomous UAV-based platform for digital asset management


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# Test cases

Concrete Column cracking Spalling

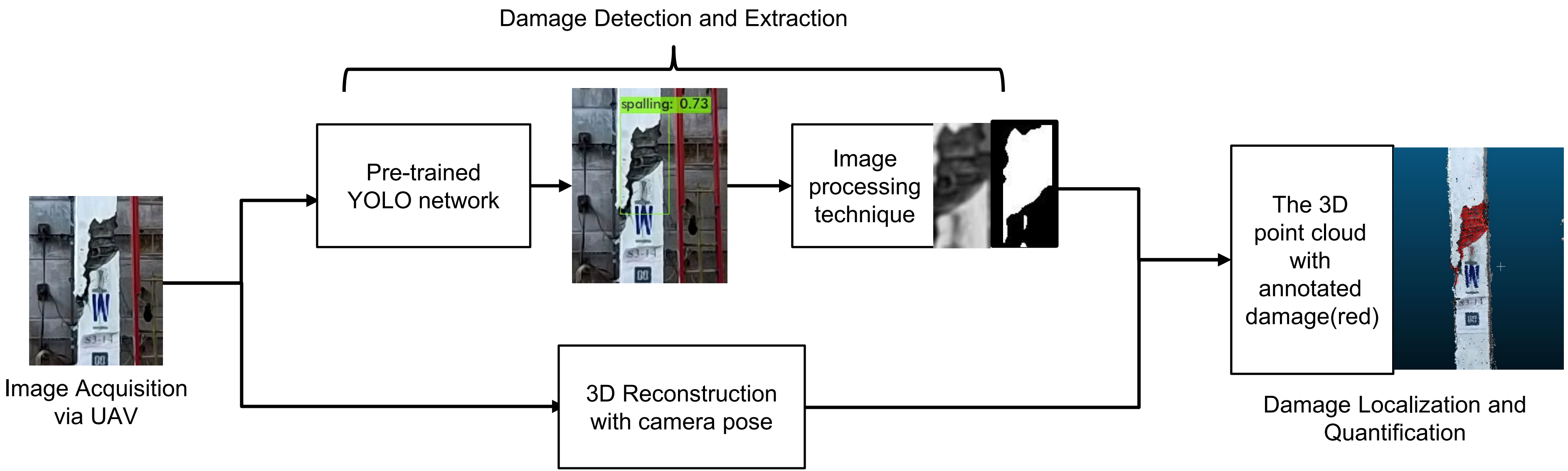
Tornado-damaged Church

Japanese viaducts

with cracks

Narazaki, Y., Hoskere, V., Chowdhary, G., \& Spencer Jr, B. F. (2022). Vision-based navigation planning for autonomous post-earthquake inspection of reinforced concrete railway viaducts using unmanned aerial vehicles. Automation in Construction

# 3D Damage Detection Approach Applied to Concrete Columns




Damage localization accuracy: 3mm
Damage size accuracy: 4.1 mm

Peng, Xin, Gaofeng Su, Zhiqiang Chen, Raja Sengupta, 2022, Structural Damage Detection, Localization, and Quantification via UAV-based 3D Imaging, 13th International Workshop on Structural Health Monitoring

# We leverage the Robot Exploration literature

- HDL Graph SLAM – A lidar-based graph SLAM system
- Octomap – An efficient probabilistic 3D occupancy grid map framework
- 3D frontier – An approach to generate candidates for NBV selection
- Rapid Random Tree – A sampling-based method to generate a collision free path from origin to destination in a complex environment
- Next Best View (NBV) planning – A map-based global planner that determines the next robot position to maximize the expected information gain (slow, 1 Hz).
- RAPPIDS planner – A memoryless local planner that generates collision-free and input-feasible trajectory based on latest sensor measurement (fast, 30 Hz)

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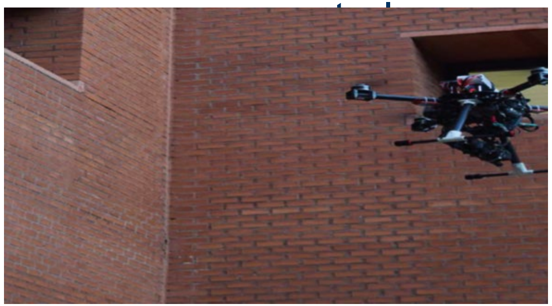
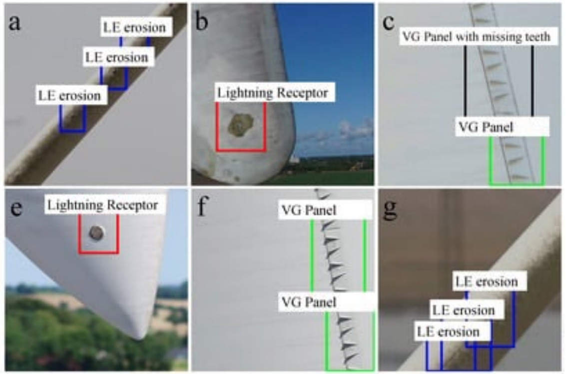
# For more autonomous UAV operation in Digital Asset Management

## Sensing-based

Detecting structural component/damage autonomously with manual or semi-autonomous



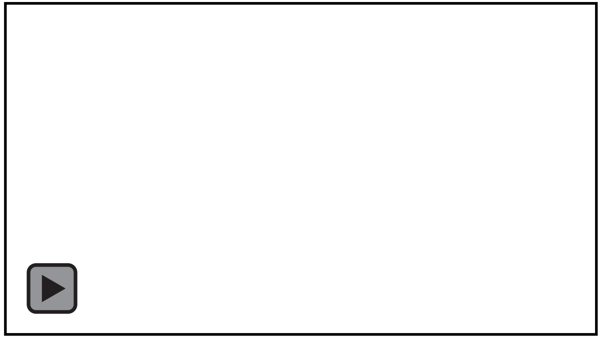
Al-Kaff et al. – Online wall detection




Anders et al. – Online damage detection

## Logic-based

Utilizing logic for specific infrastructure to control UAV autonomously



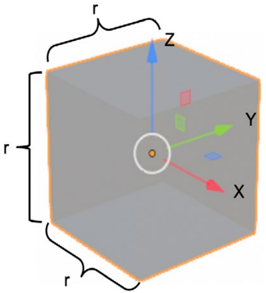
Spencer et al.– Column size assumption

Sengupta et al. – Linear structure assumption

# Problem Formulation

Discretize 3D space into a set of cubes r x r x r.

**2r = Resolution specification**




**Specified 3D volume**

Unknown 3D structure

### Accuracy

Point cloud map VS Ground truth model

$$\text{Error} = \sum_{i=1}^{N} Point\ to\ plane\ dist\ \ (p_i, q_j)$$

Error < resolution r

### Completeness

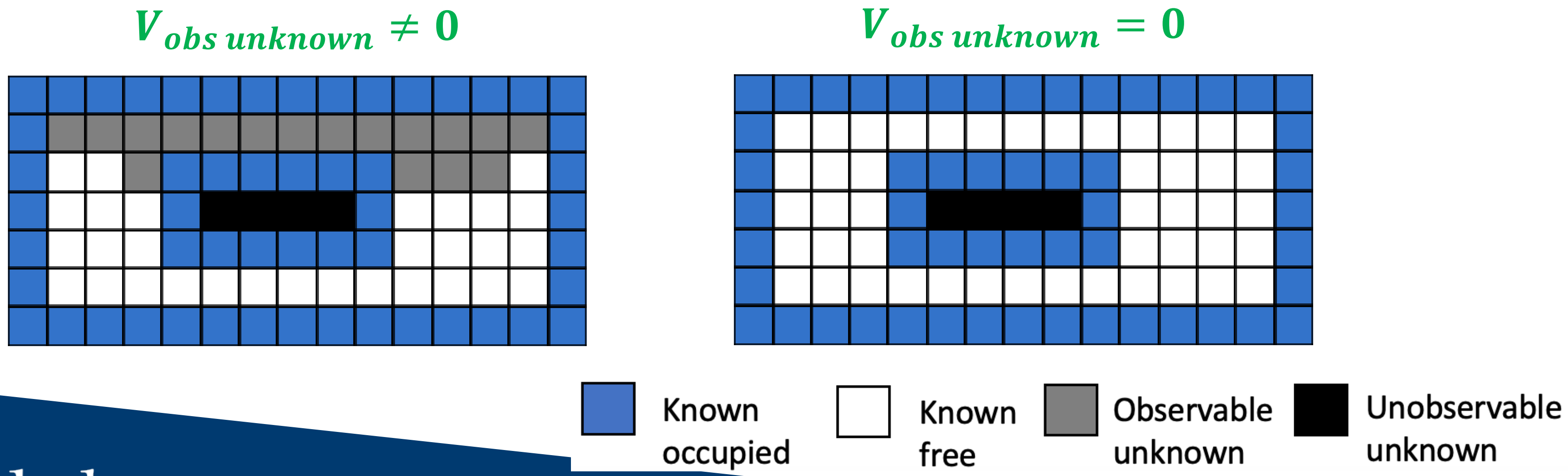
Occupancy grid map VS Ground truth model

$$\text{Completeness} = \frac{V_{known}}{V_{observable}}$$

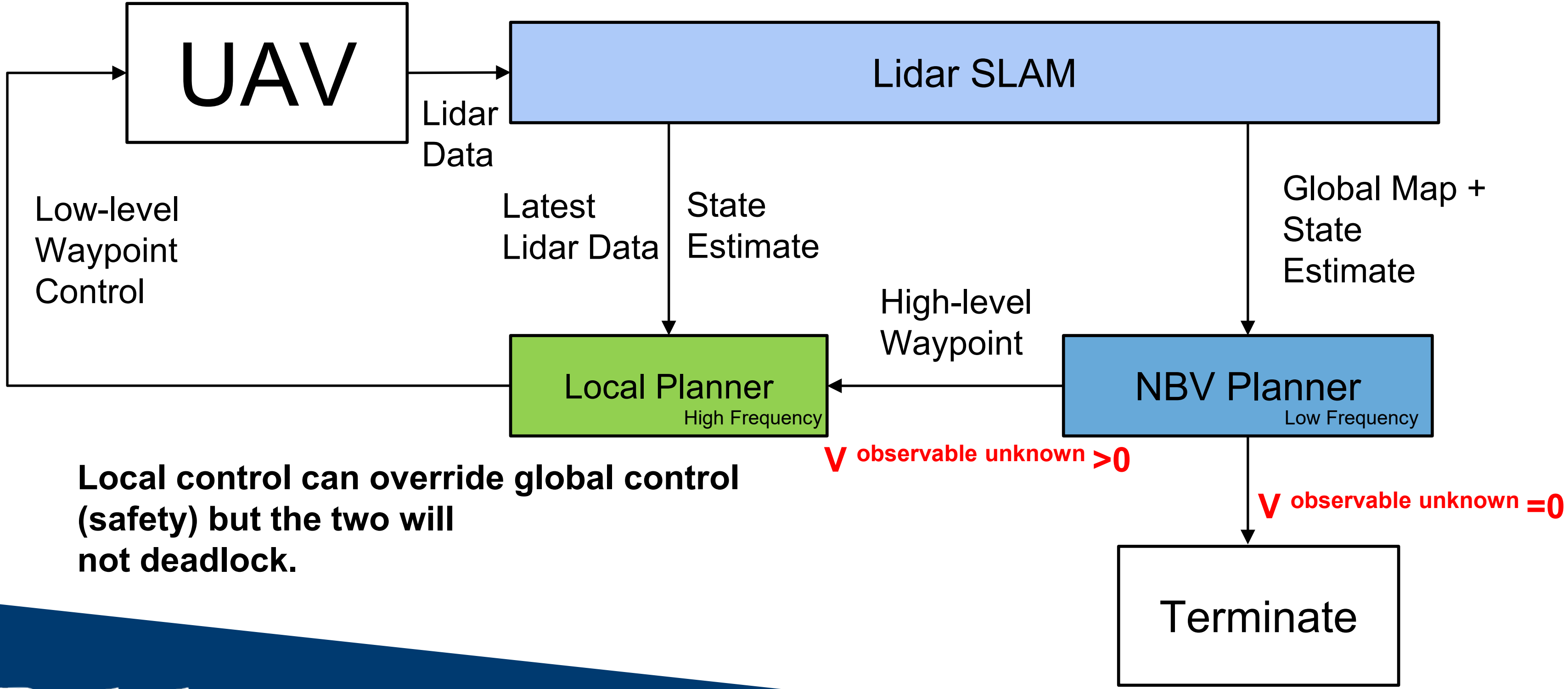
Completeness → 1

# Problem formulation

A 3D bounded space V is initially unmapped, $V = V_{unknown}$. We aim to determine which parts of V are free $V_{free}$ or occupied $V_{occ}$ with a robot carrying 3D lidar sensor. There exists part which are unobservable due to the UAV constraints, $V_{unobs\ unknown}$. The exploration problem is considered fully solved when $V_{free} \cup V_{occ} = V \setminus V_{unobs\ unknown}$, which is $V_{obs\ unknown} = 0$.



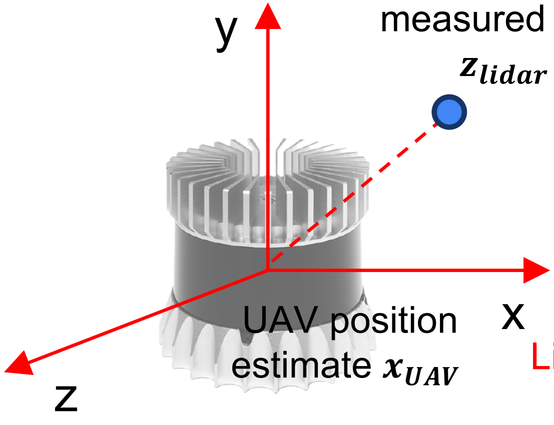
# Design: Hierarchical Planner and Control




**Local control can override global control (safety) but the two will not deadlock.**

# Validation by Simulation: Regional Scale Autonomous Swarm Damage Assessment (RSASDA) simulator

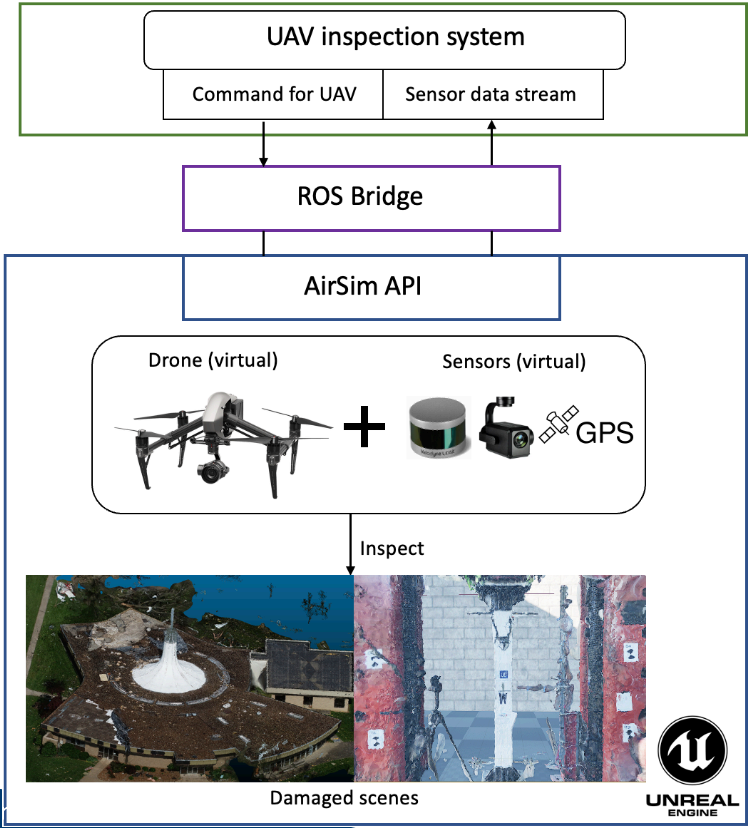
## Lidar error model




Lidar measurement error

$$z_{pt} = x_{UAV} + z_{lidar} = x^{gt}_{UAV} + e_{UAV} + z^{gt}_{lidar} + e_{lidar}$$

UAV pose estimate error




Peng, X., Su, G., Chen, Z., & Sengupta, R. (2022, June). A Vir-
tual Reality Environment for Developing and Testing Autono
UAV-Based Structural Inspection. In European Workshop on Struc-
tural Health Monitoring (pp. 527-535)

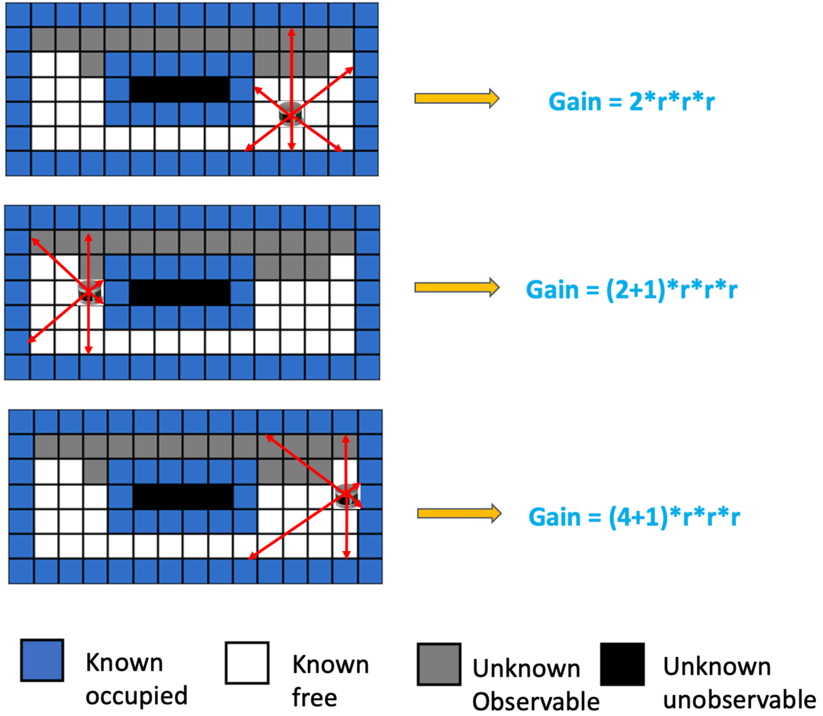
# The local planner has been validated by Professor Mueller at RFS, meaning the integrated system can be safely tested by PEER

# NBV global planner

A sample-based greedy algorithm iteratively finds the NBV that maximizes average volumetric gain per unit UAV travel distance. However, this global planner, based on the entire environment map, run at a low frequency.

**Algorithm 1** NBV selection algorithm

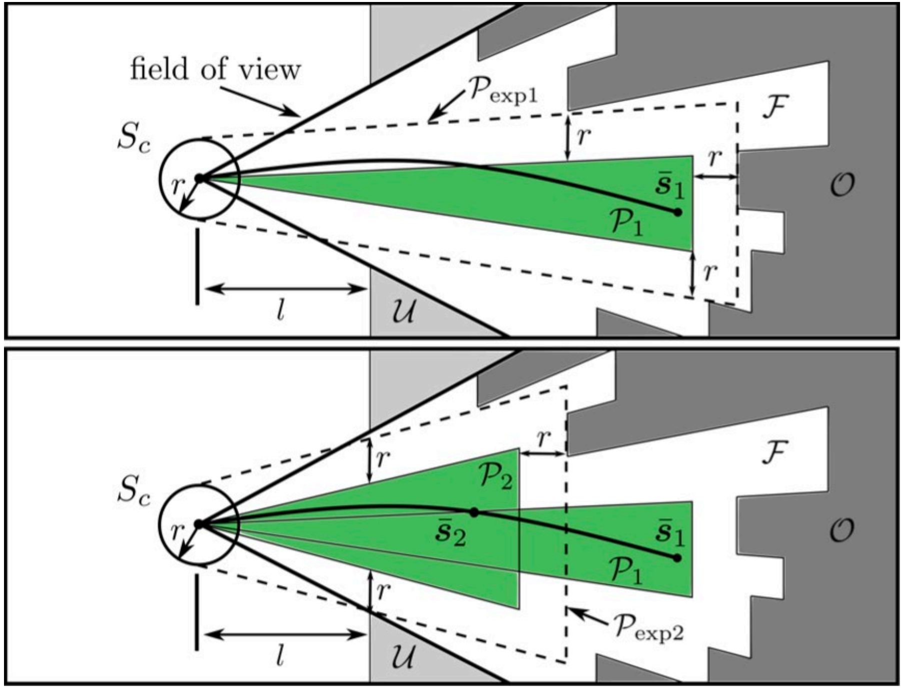
**Require:** Map $M_t$; configuration $\xi_t$; safety distance $d$
  Frontier set $X \leftarrow ObtainFrontier(M_t, d)$
  $X \leftarrow sample(X, N)$
  $Gain_{best} \leftarrow 0$
  $\sigma_{best} \leftarrow \phi$
  **for** NBV candidate $\xi_i$ in $X$ **do**
    $\sigma_i \leftarrow RRTstar(M_t, \xi_t, \xi_i)$
    $Gain_i \leftarrow VolumetricGain(M_t, \sigma_i)$
    **if** $Gain_i > Gain_{best}$ **then**
      $\sigma_{best} \leftarrow \sigma_i$
      $Gain_{best} \leftarrow Gain_i$
    **end if**
  **end for**
  **return** $\sigma_{best}$




Xin Peng, Gaofeng Su, Benjamin Folk, ZhiQiang Chen, Raju Sengupta, “ Autonomous UAV-based structural damage exploration platform for post-disaster reconnaissance”, ASCE International Conference on Computing in Civil Engineering, 2023

# **Local planner** – Rectangular Pyramid Partitioning using Integrated Depth Sensors (RAPPIDS)

- Directly plan using the latest depth images from depth camera/lidar
- Sample many trajectories as candidates
- Decompose free space into a collection of collision-free pyramids – fast to detect collision
- Iterate through candidates: Input feasible ? → Velocity admissible ? → Collision free ? → Lowest cost (distance between trajectory end point and goal) ?

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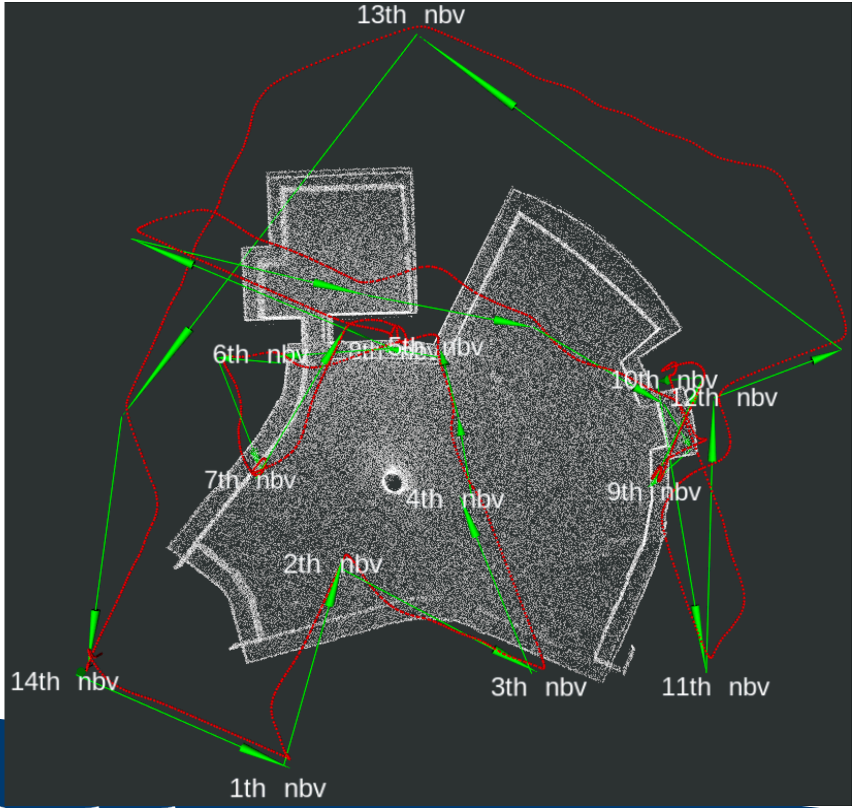
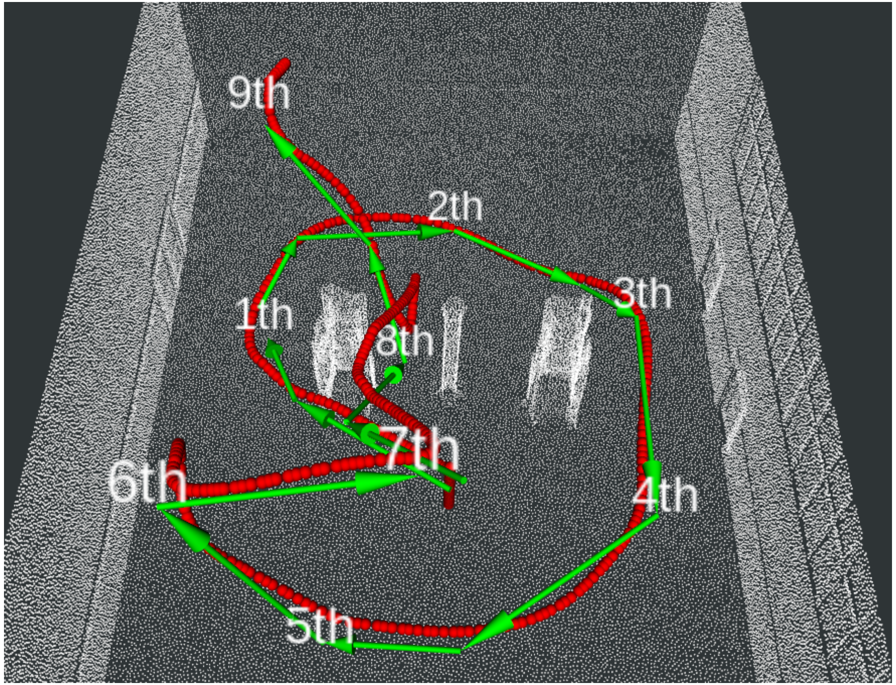
N. Bucki, J. Lee, and M. W. Mueller, "Rectangular pyramid parti- tioning using integrated depth sensors (rappids): A fast planner for multicopter navigation," *IEEE Robotics and Automation Letters*, vol. 5, no. 3, pp. 4626–4633, 2020.

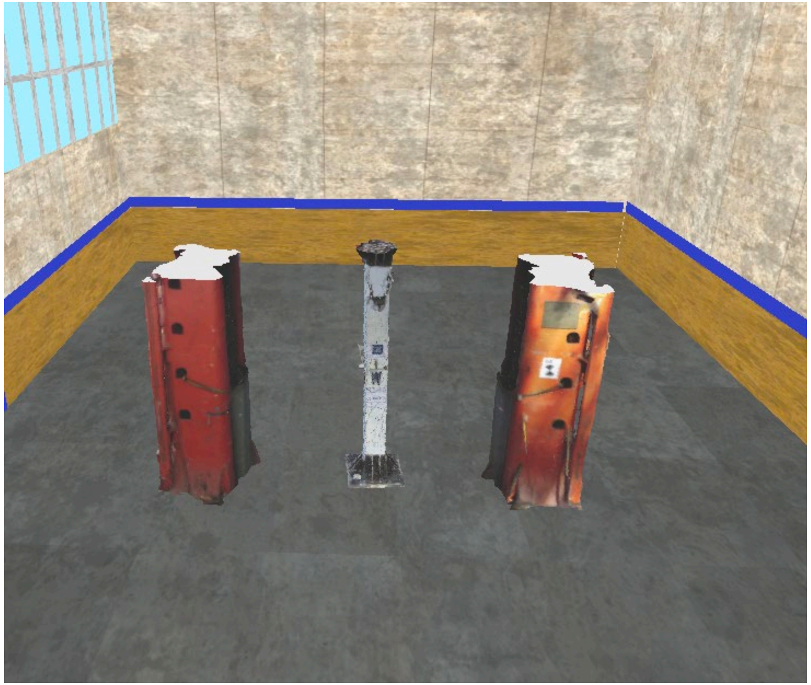
# Experiment - church

# Results

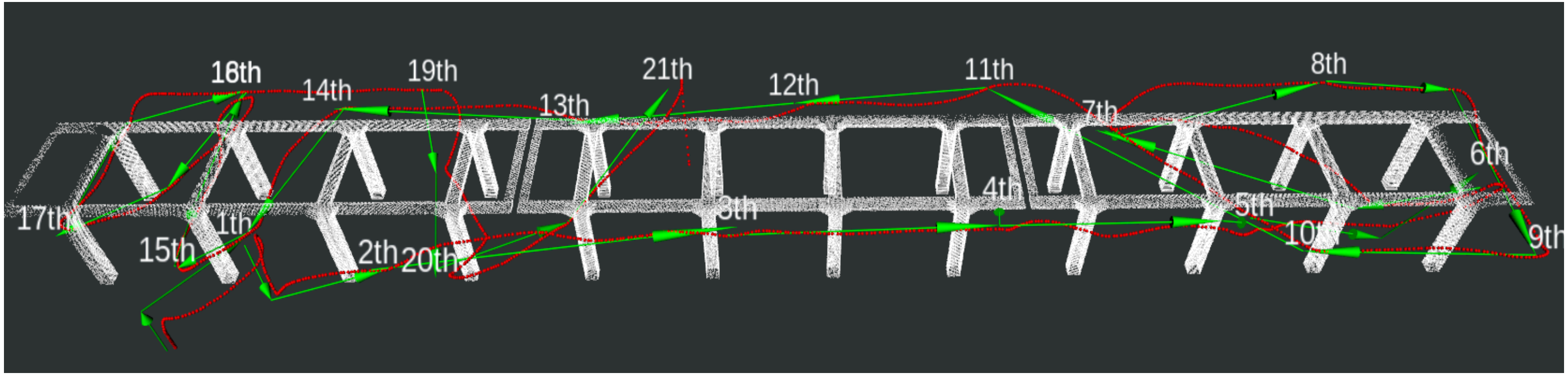

13th nbv
6th nbv
5th nbv
10th nbv
12th nbv
7th nbv
4th nbv
9th nbv
2th nbv
14th nbv
3th nbv
11th nbv
1th nbv

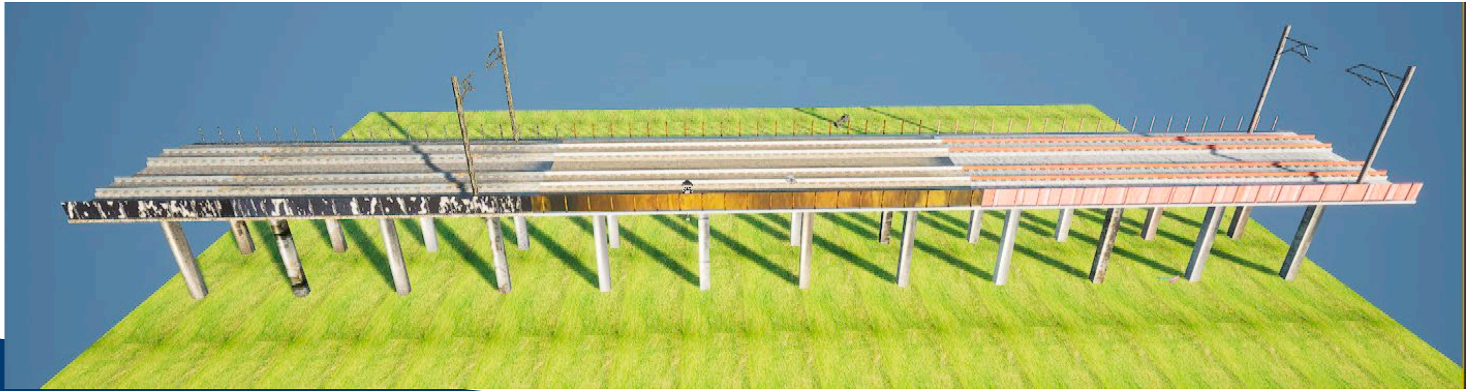
# Results



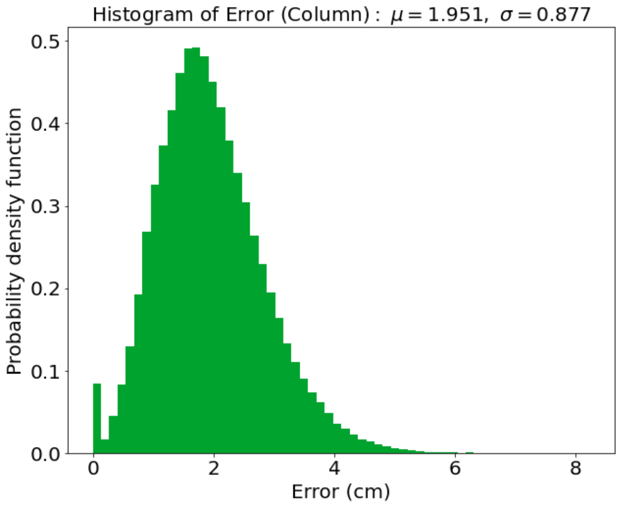
# Results

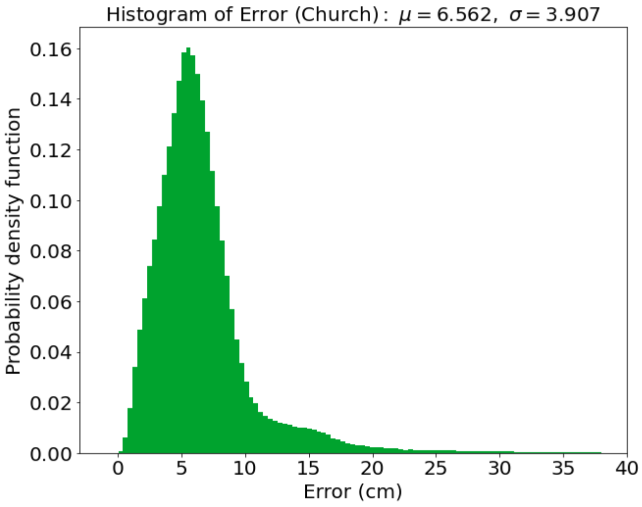


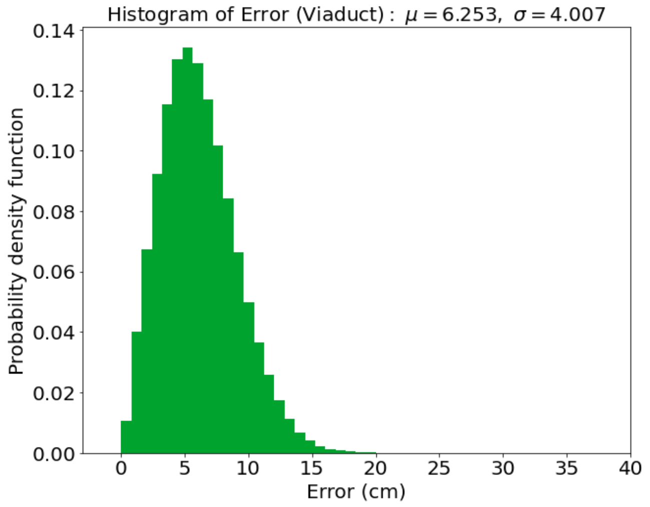



Narazaki, Y., Hoskere, V., Chowdhary, G., \& Spencer Jr, B. F. (2022). Vision-based navigation planning for autonomous post-earthquake inspection of reinforced concrete railway viaducts using unmanned aerial vehicles. Automation in Construction

# Results - accuracy




**Resolution r = 7.5 cm**
**Accuracy ≈ 1.95 cm**
**Completeness ≈ 1**
**Flight length: 81 m**
**Time: 2 mins 7 seconds**

**Resolution r = 40 cm**
**Accuracy ≈ 6.7 cm**
**Completeness ≈ 1**
**Flight length: 530 m**
**Time: 7 mins**

**Resolution r = 40 cm**
**Accuracy ≈ 6.2 cm**
**Completeness ≈ 1**
**Flight length: 546 m**
**Time: 6 mins 44 seconds**

# Conclusions and Future Work

- Designed a more autonomous UAV-based digital asset management technology that images to a specified resolution. Evaluated completeness, reconstruction error, flight distance and time in Simulation.

Recommendations to PEER:

- Test fly the uniform resolution system during an experiment at the Big Press
- Collaborate with Caltrans to speed up inspection time by embedding inspection intelligence into the Autonomy. Variable resolution imaging.