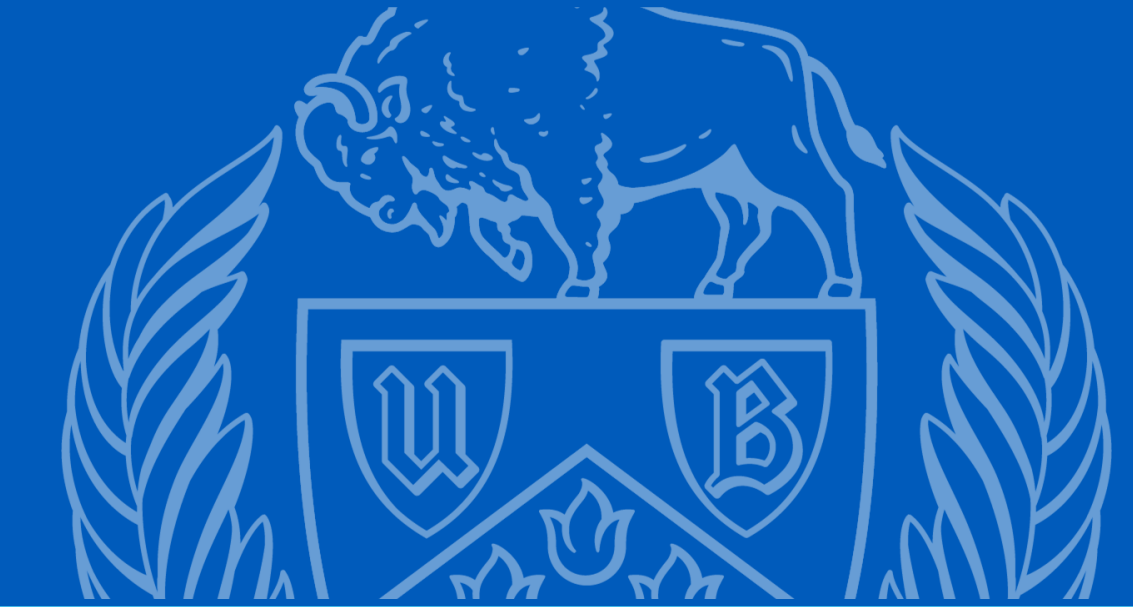


# Enhanced Visual Perception for Autonomous Spacecraft Navigation

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## Motivation

- Autonomous spacecraft use visual cameras for Terrain Relative Navigation (TRN) and Entry, Descent, and Landing (EDL) maneuvers
- Current state-of-the-art methods restricted to template matching approaches due to limited processing power and memory constraints
- Adoption of Tensor Processing Units (TPUs) as onboard co-processors enables more advanced computer vision techniques (e.g. deep learning)
- Space introduces unique perceptual challenges, including poor and dynamic lighting conditions, feature sparsity, and training data availability

## Surface-to-Orbit View Generation

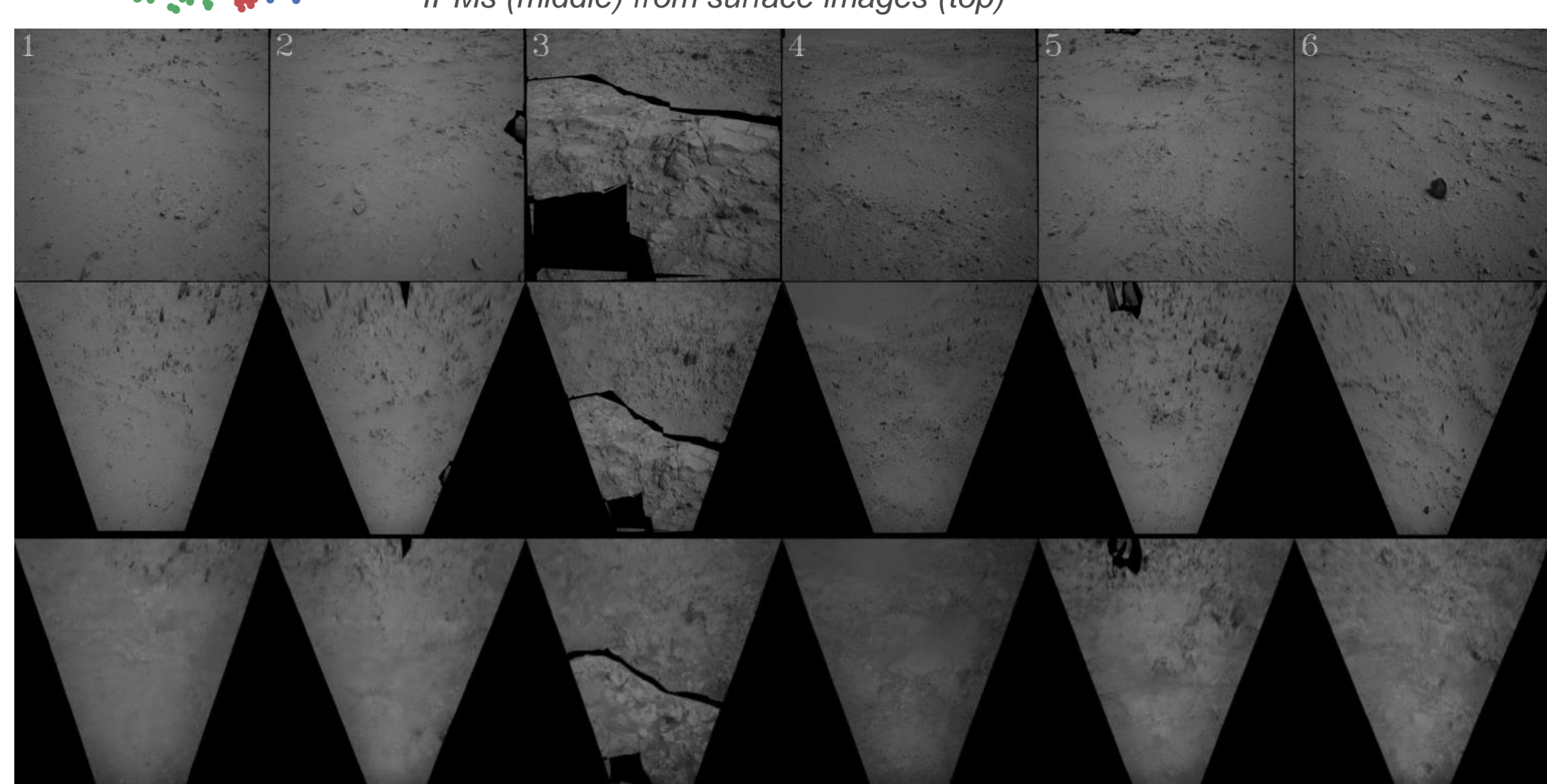
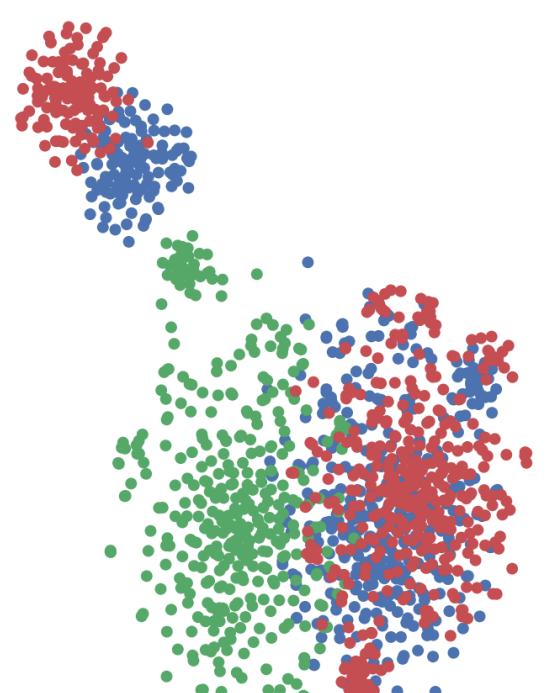
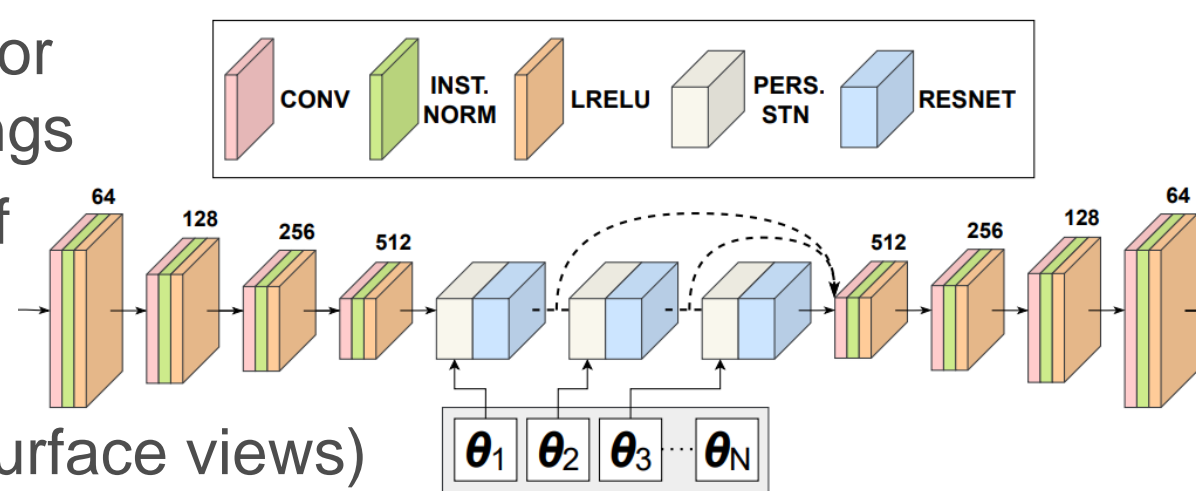
**Goal:** Use semantic segmentation for hazard detection during Mars landings

**Problem:** requires large amounts of training data, hard to come by

- Do not have labelled datasets from previous Mars Rover missions (surface views)
- Inverse Perspective Mapping (IPM) can transform image to bird's-eye view, induces unnatural pixel stretching and blurring

- Solution:** Use a generative model to improve the appearance of IPMs
- Incremental perspective transformations reduce pixel deformation
  - Spatially-constrained and feature-consistent objective function retains surface ground truth

*Top:* generator architecture of our model. *Left:* t-SNE visualization of feature distributions between the surface (red), IPM (green), and our model (blue). *Bottom:* examples of generated views (bottom row) compared with IPMs (middle) from surface images (top)



## Efficient Feature Matching

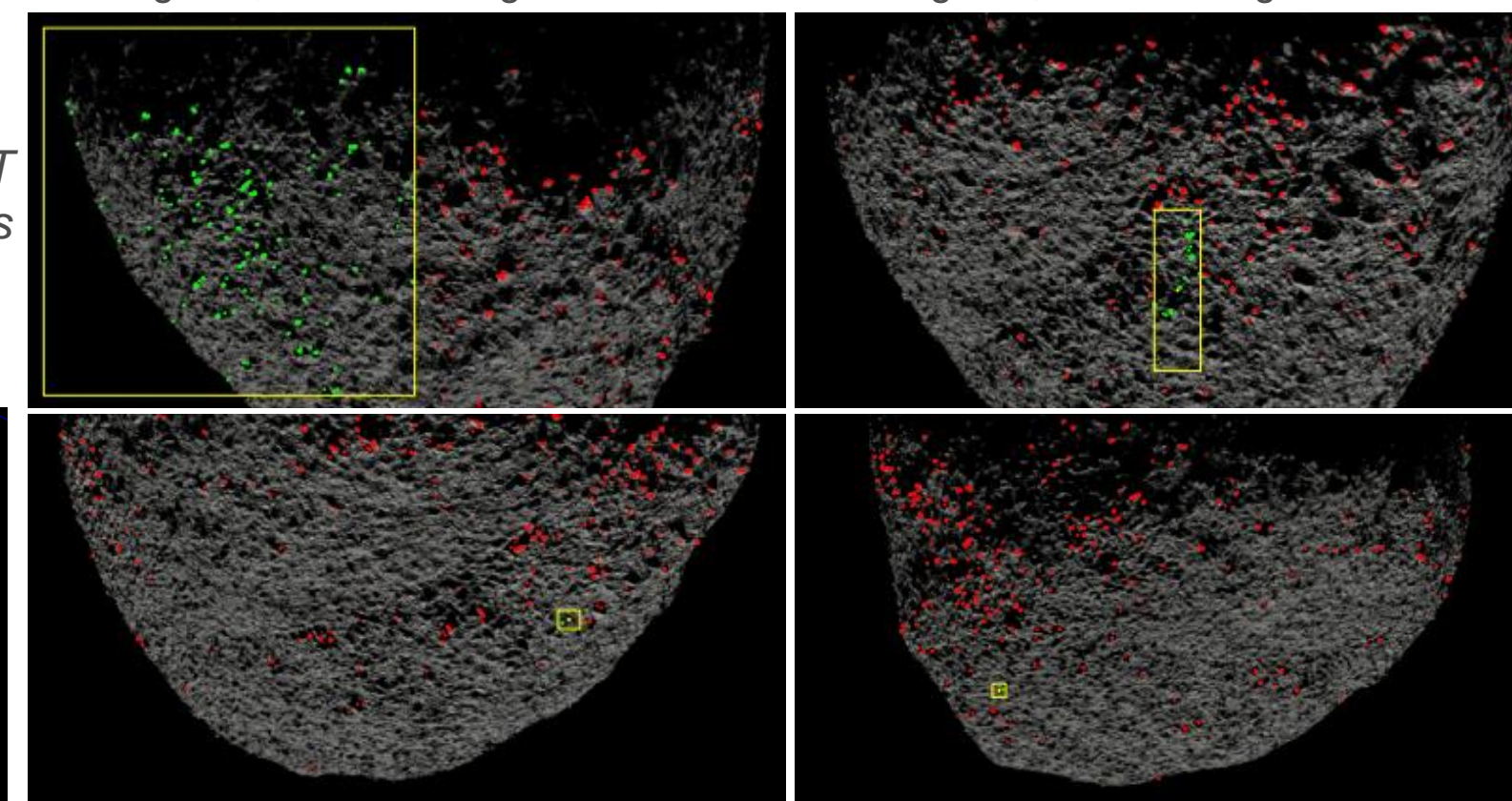
**Goal:** Use traditional image processing features (e.g. SIFT, SURF, ORB) for asteroid mapping during TRN

**Problem:** Feature matching process has high computational expense and poor accuracy when observing asteroids

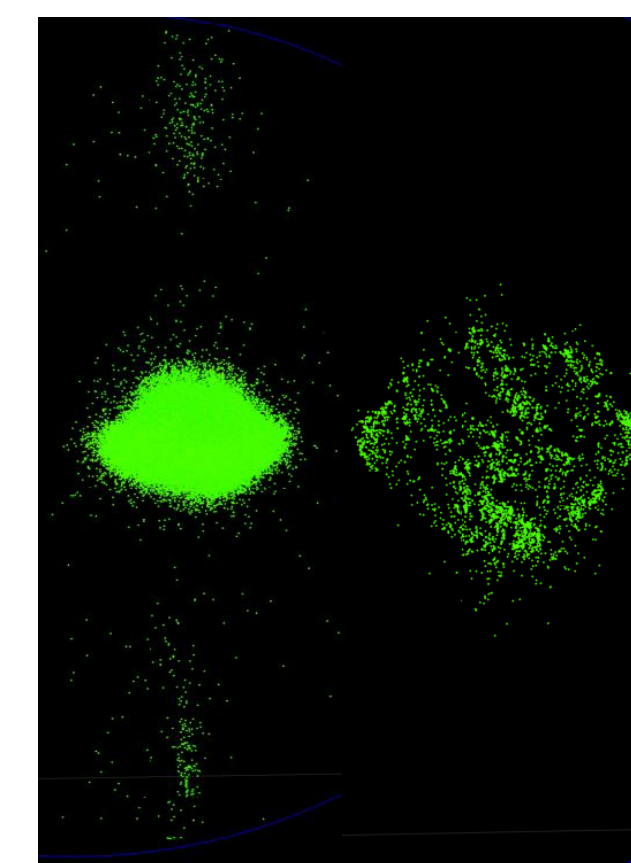
**Solution:** Use vehicle state to restrict the set of matching candidates through Multiple Hypothesis Testing (MHT)

- Recursive least squares estimates each feature position in the *asteroid-fixed* frame
- Vehicle state information (i.e. position, orientation) is used to determine which features are visible in the current frame
- MHT produces a rectangular region (gate) around each feature which converges over time as estimates improve
- Reduces number of features considered for matching only to those within the gate

Image 10, 224 matching candidates      Image 25, 35 matching candidates

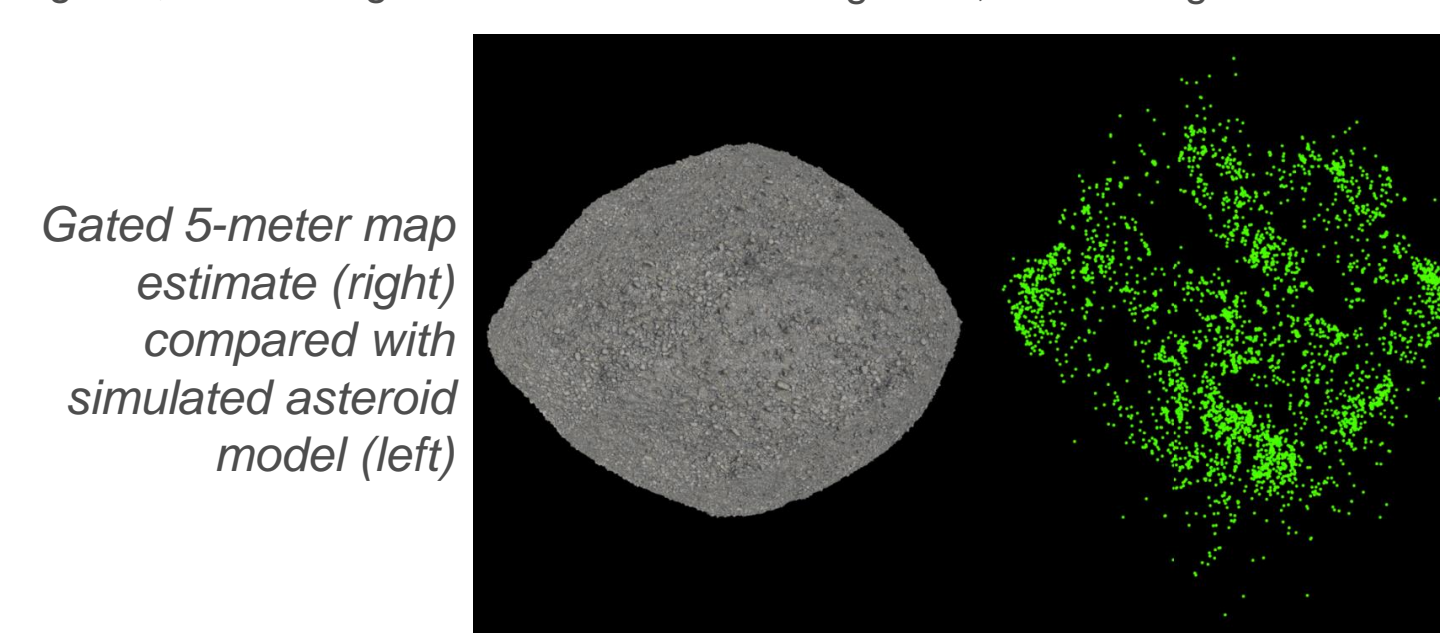


Gates produced by MHT around ORB features

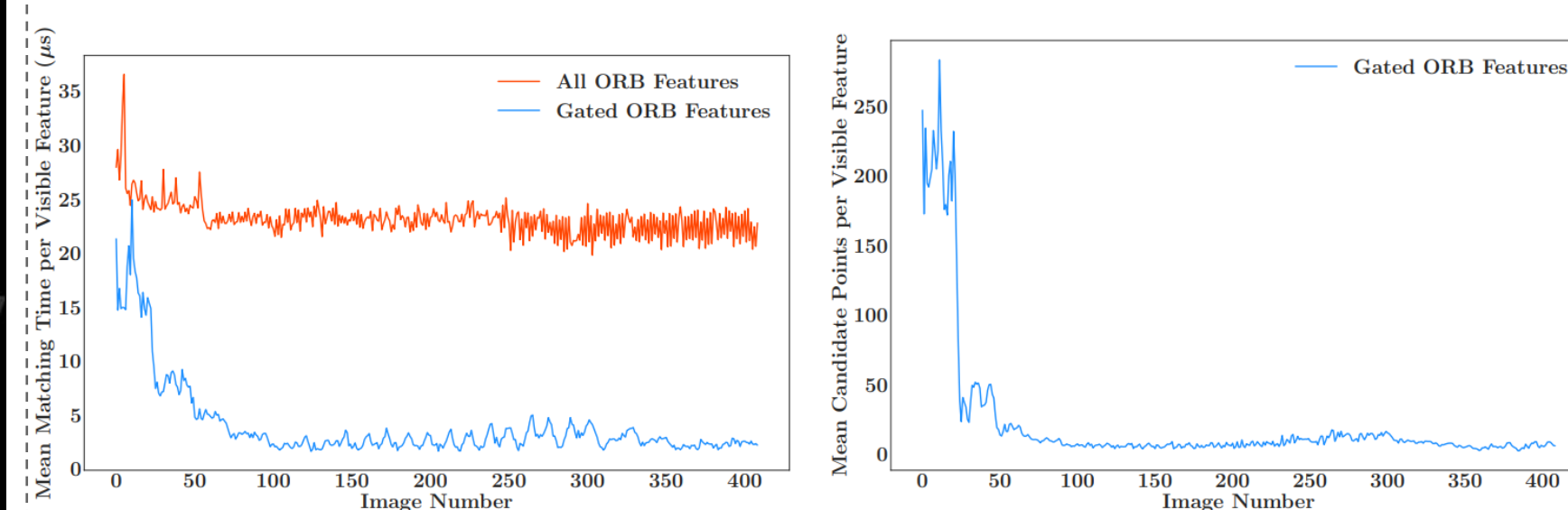


Non-gated (left) vs gated (right) final map of ORB features estimated at 5 meters or below

Image 50, 1 matching candidate      Image 100, 1 matching candidate



Gated 5-meter map estimate (right) compared with simulated asteroid model (left)



Gated vs non-gated matching times (left) and number of matching candidates (right) of ORB features

Chris Gnam, Timothy Chase Jr, Karthik Dantu, John Crassidis, "Efficient Feature Matching and Mapping for Terrain Relative Navigation Using Hypothesis Gating", *AIAA SciTech Forum*, January 2022

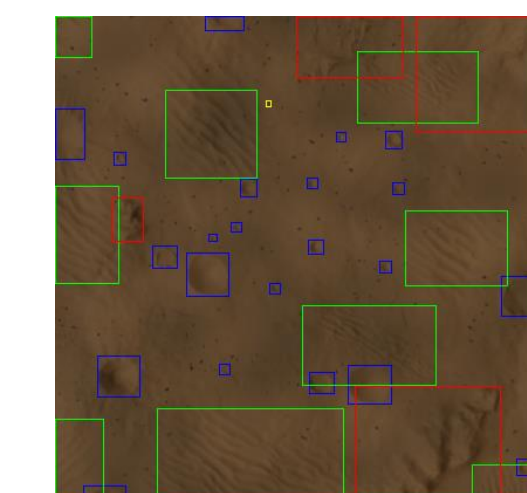
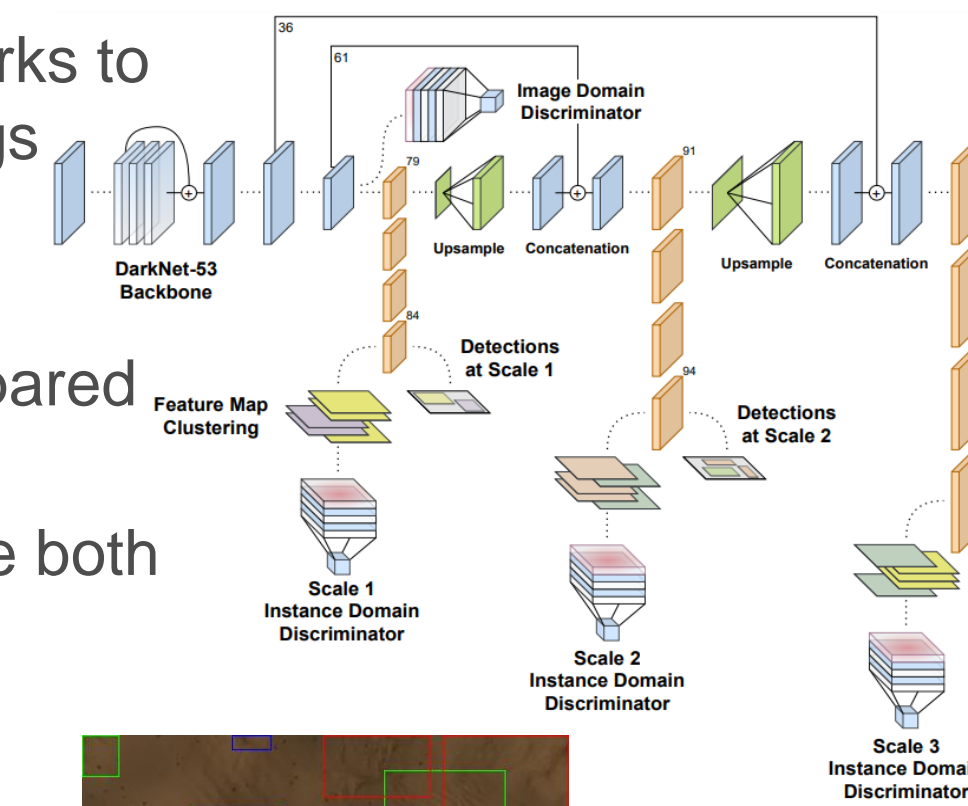
## Hazardous Terrain Detection

**Goal:** Use modern object detection networks to find hazardous terrain during Mars landings

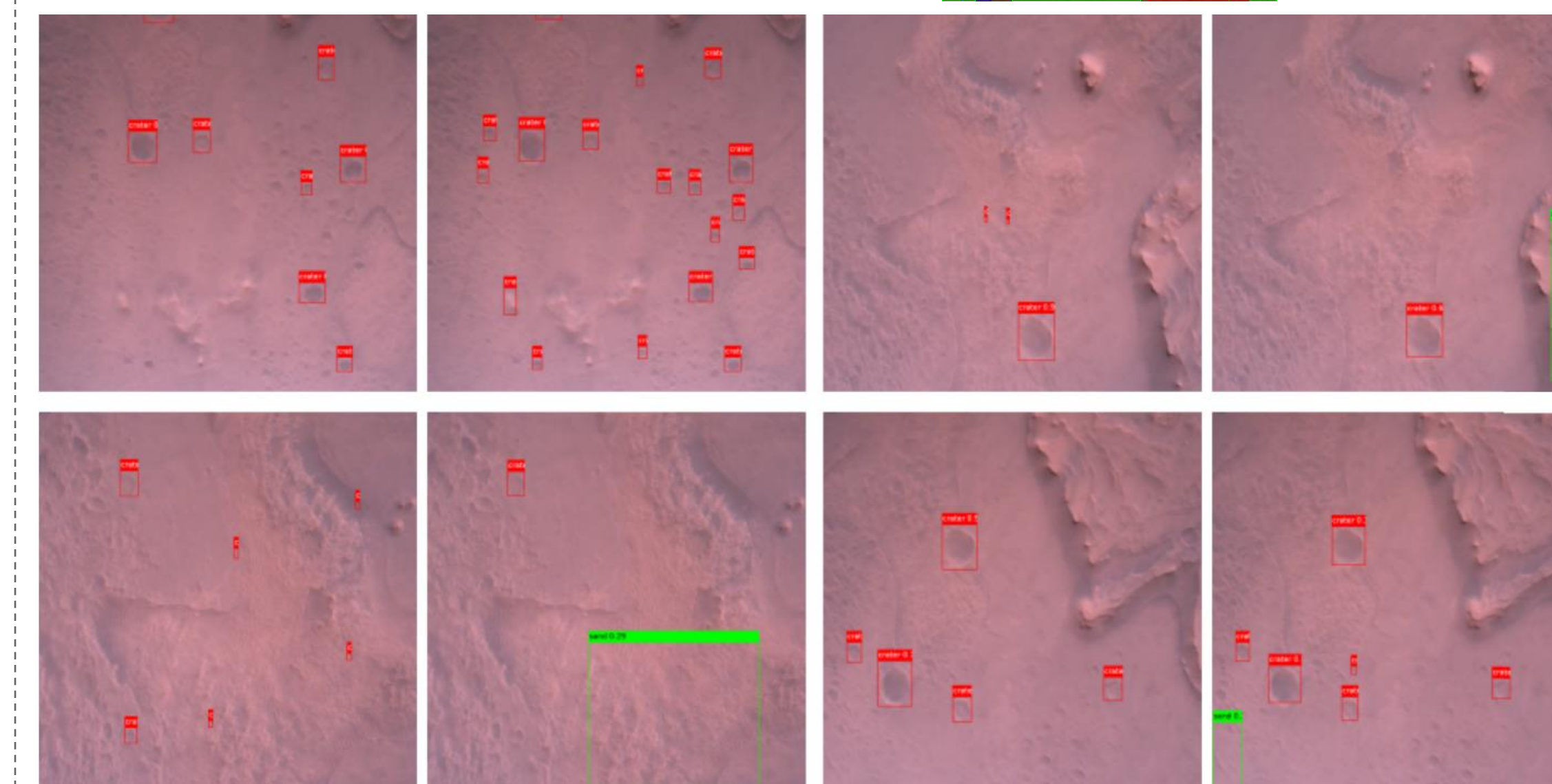
**Problem:** No training data and extremely feature-sparse images

**Solution:** Use domain adaptation to tackle both problems simultaneously

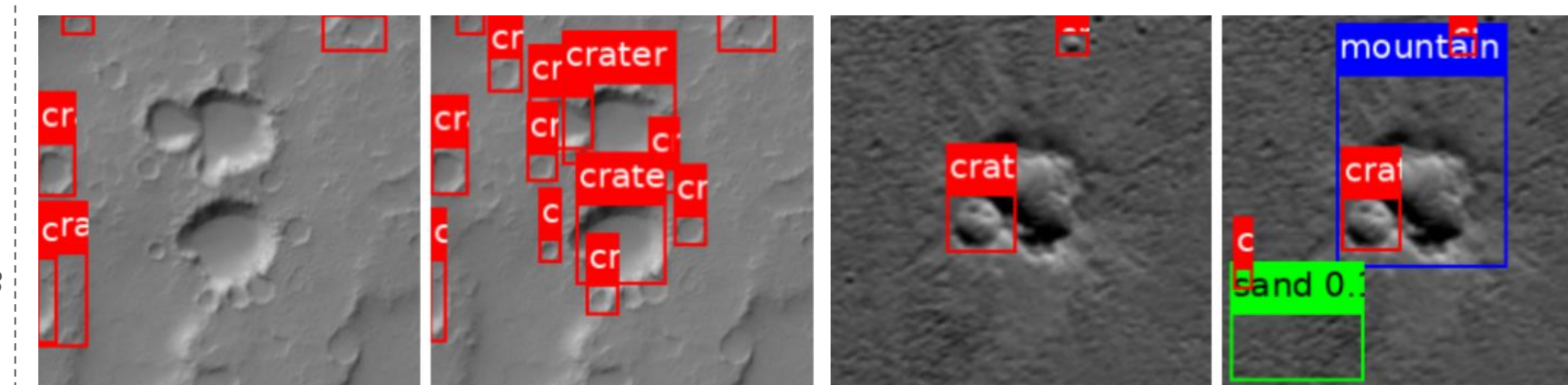
- Less edge and intensity gradients compared with terrestrial environments
- Model trained in simulation with unlabeled real-world (target) data
- Domain discriminators used to discern real and simulated features
- Visual similarity-based clustering before aligning object (instance) features to improve feature-sparse performance



*Top:* Model architecture. *Left:* Example of a simulated image used to train the model



*Top:* Detections between YOLOv3 (left) and our model (right) on images captured during the Mars Perseverance Rover landing. *Bottom:* Detections between YOLOv3 (left) and our model (right) on images captured from the Mars Reconnaissance Orbiter. Red boxes represent crater detections, green represents sand, and blue represents mountain.



Timothy Chase Jr, Chris Gnam, John Crassidis, Karthik Dantu, "You Only Crash Once: Improved Object Detection for Real-Time, Sim-to-Real Hazardous Terrain Detection and Classification for Autonomous Planetary Landings", *AAS/AIAA Astrodynamics Specialist Conference*, August 2022