Machine Learning in Space: Seeker-1's Intelligent Vision System

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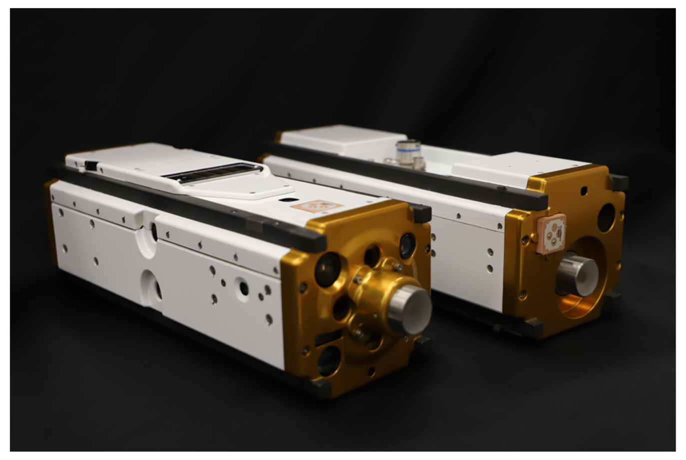
Mission Overview


Seeker-1 (left) & Kenobi (right)
Credit: NASA


Northrop Grumman Enhanced Cygnus Spacecraft
Credit: NASA

- Seeker-1 is a NASA JSC mission to demonstrate technologies relevant to on-orbit inspection & servicing
- Seeker-1 (a 3U CubeSat) will be deployed from an Enhanced Cygnus cargo vehicle in Summer 2019
  - Will perform relative motion experiments around Cygnus
- UT-developed computer vision algorithms must detect and estimate the relative bearing of Cygnus
  - Must be done at > 1 Hz (with CPU only)
  - Must be robust to varied lighting conditions, any target orientation, and against varied backdrops
  - Must be flight-ready and integrated with the Seeker-1 GNC system

Research Background

Space-Based Computer Vision

- The space environment presents many difficulties with respect to computer vision:
  - Clouds and Earth generate complex noise patterns
  - Lighting is inconsistent and can easily blind the camera or illuminate only half an object
  - Low computing power and time constraints can eliminate many solutions viable for Earth-based systems
- Non-cooperative spacecraft have no reflectors or lights to make detection easier

"Intelligent" Cameras on Earth

- Convolutional neural network (CNN) architectures have emerged as capable image classifiers
  - More resilient than classical computer vision algorithms in diverse environmental conditions
- CNNs are increasingly used in autonomous applications
- Open-source deep learning frameworks (TensorFlow, PyTorch, etc.) have become very powerful and popular

Methodology

Neural Network Architecture & Training

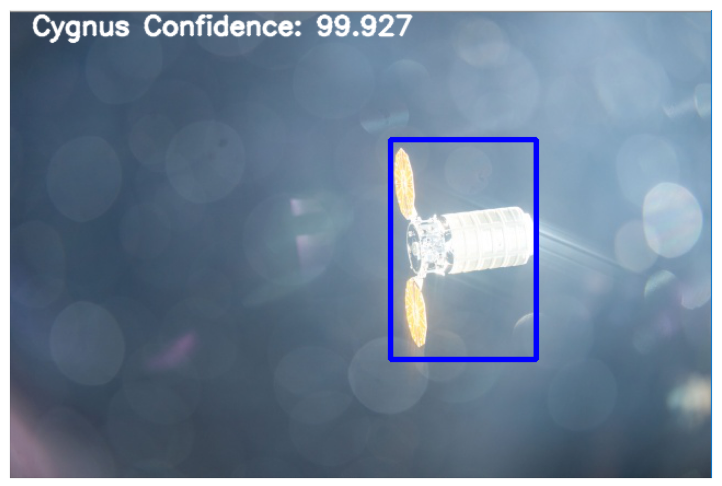
- Single Shot Detector (SSD) meta-architecture chosen for speed and image processing capabilities
- Selected Google's MobileNet SSD v1 architecture[1] for lightweight object detection and localization
- Iteratively trained network on real images from the ISS and images synthetically generated in Unreal Engine
  - Conducted via TensorFlow's Object Detection API[2]
- Synthetic images allowed us to train on orientations for which no real images existed


Image of Cygnus from ISS
Credit: NASA

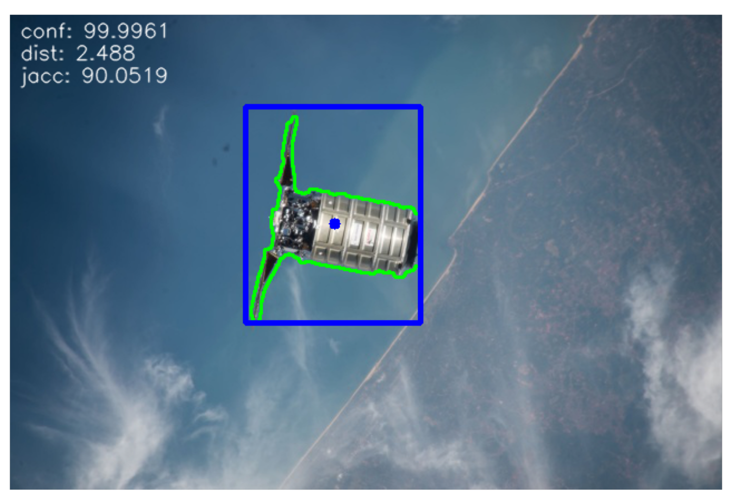

Simulated Image of Cygnus
Credit: UT-Austin

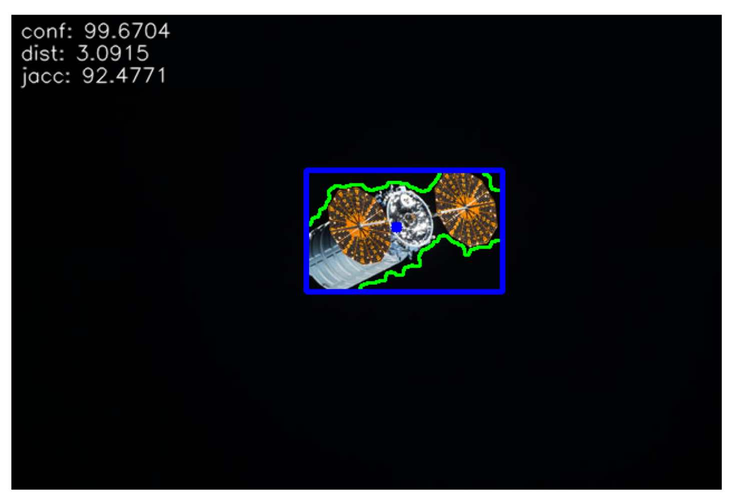
Target Detection & Relative Az./El. Estimation

1. The trained MobileNet SSD detects and bounds Cygnus if it is present

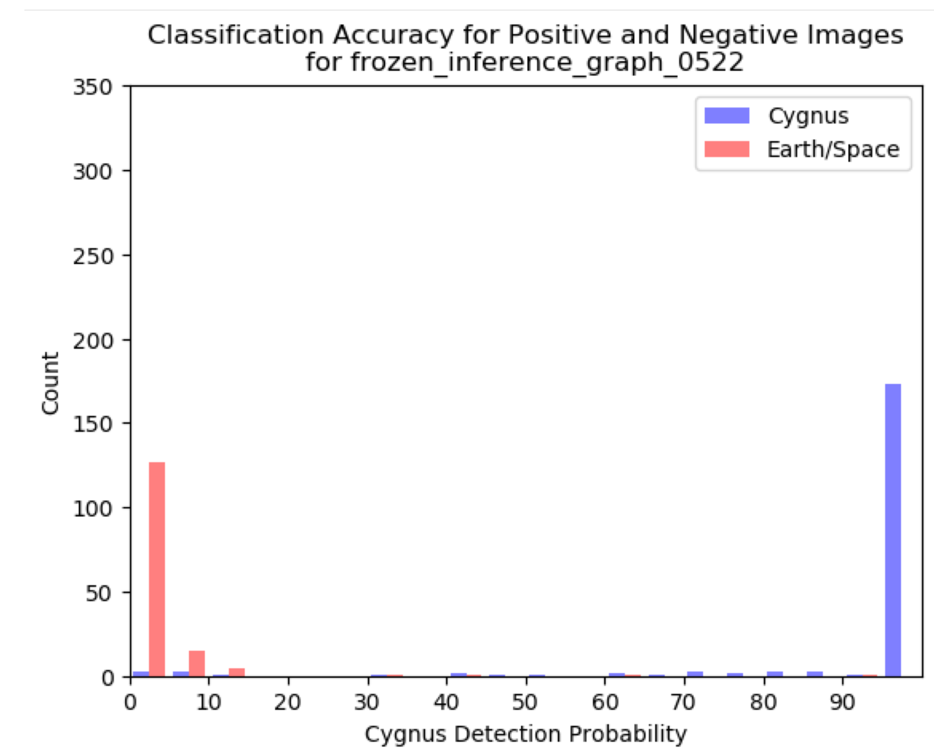


2. Contouring algorithms segment the spacecraft body within a localized region
3. The centroid is computed using the first moment of area
4. Relative azimuth and elevation computed from centroid and camera intrinsics





Results



Metric	Validation Set	Test Set
Detection Rate	0.990	0.965
False Positive Rate	0.047	0.027
False Negative Rate	0.010	0.035
Jaccard Coefficient	0.890	0.888

Solutions Generated at ~3-4 Hz on Intel Joule 570X Flight Computer

Conclusions & Future Work

- CNNs are a valid approach to the detection/localization problem, even with limited computational power
- Contouring is difficult against a cloudy/noisy Earth
- Higher-fidelity simulated visuals may improve CNN training
- UT continuing partnership with NASA JSC to research the viability of CNNs for:
  - Full semantic/instance segmentation
  - 6-DOF relative pose estimation

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