Real-Time Satellite Component Recognition with YOLO-V5

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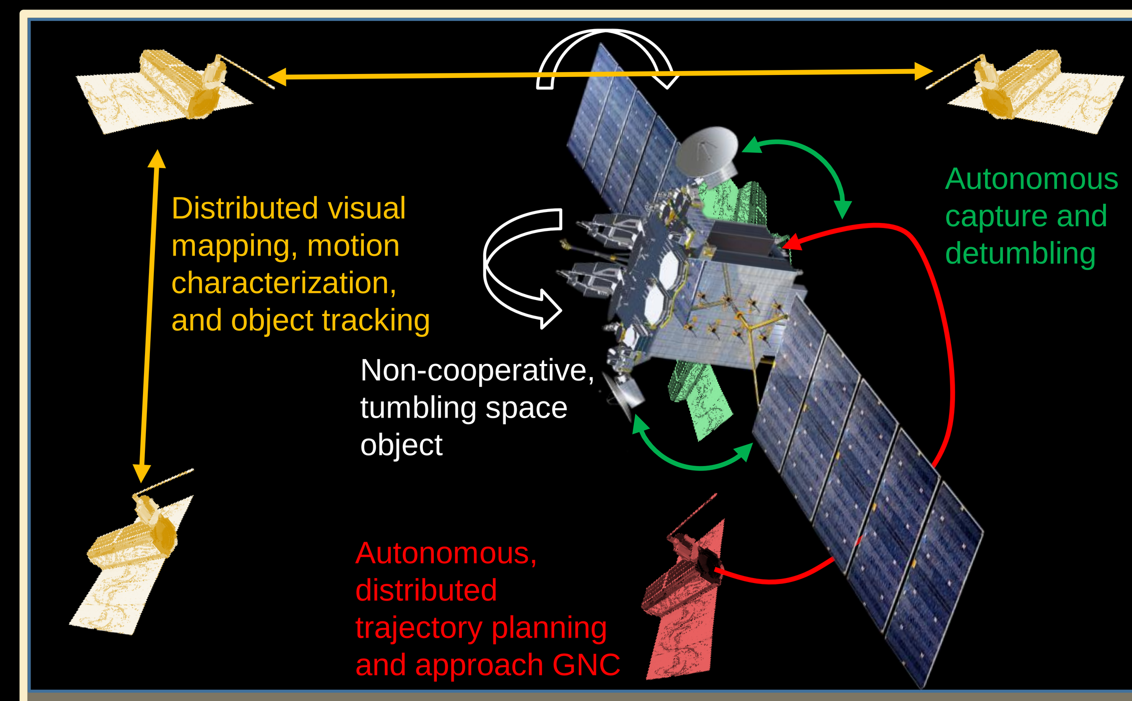
INTRODUCTION

- Demand for collision avoidance, on-orbit servicing and capture of non-cooperative space object (target satellite) has been growing with the increasing amount of space debris
- Use of swarm satellites for in-space inspection and capture of non-cooperative targets is a viable solution to tackle this problem
- The focus of this research is to use Machine Learning algorithm – You Only Look Once (YOLOV5) to autonomously classify and locate target satellite components such as solar panels, antennas, thrusters and the satellite body in real-time space missions
- The features identified can then be used to guide capturing satellites around collision hazards (solar panels, antennas) towards capture locations (thruster nozzles, body panels)

Concept Overview



PRE-PROCESSING METHODS

- Randomly crop between 0 and 34% of the image
- Random rotation of between -28° and +28°
- Random brightness adjustment of between -49% and +49%
- Random Gaussian blur of between 0 and 10 pixels
- Salt and pepper noise (dark spots in white regions and white spots in dark regions) was applied to 13% of pixels

OBJECTIVES AND REQUIREMENTS

1. Develop proof-of-concept of using Machine Vision to classify and identify satellite features
2. Characterize performance of the algorithm in hardware-in-the-loop experiments with different lighting conditions
   - The algorithm shall be able to identify and track each feature on the satellite in real-time
   - The algorithm shall be able to run with realistic hardware performance constraints
   - The algorithm shall not require any assistance from the target satellite

METHODS

Training Data: Publicly available satellite images from the internet, satellite models used in Kerbal Space Program, and geometric models used in AGI Systems Tool Kit (STK) were gathered and annotated.

Testing Data: Videos of target satellite taken by a chaser satellite at the ORION lab [1] with different lighting conditions and different target and chaser approach orientations.

Algorithm: Ultralytics YOLO V5 model [2] with genetic algorithm hyperparameter tuning and several image pre-processing augmentation techniques.

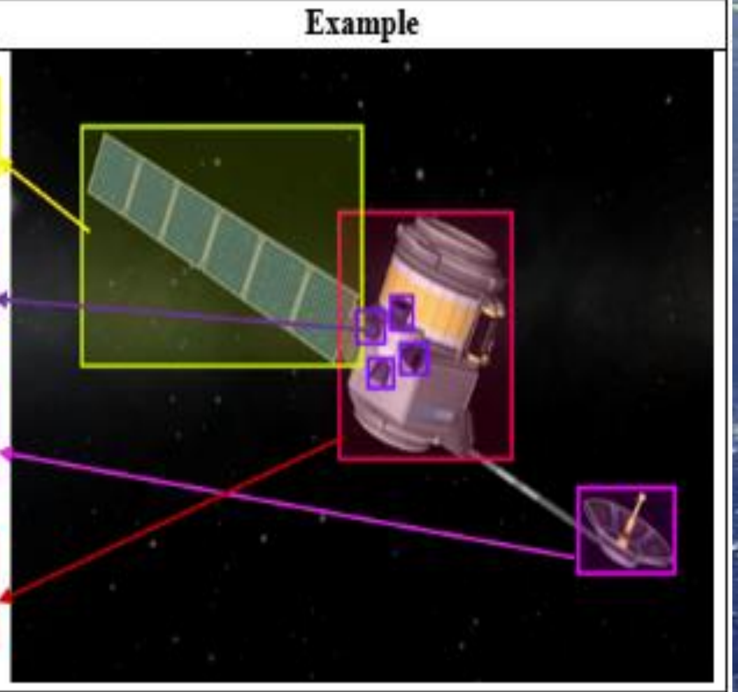
CONCLUSION

Based on initial testing of YOLO V5 on the satellite dataset developed by the ORION lab, test video observation, analysis and results discussed in this paper, real-time detection of different components of a non-cooperative space object is feasible. Since the algorithm is not completely reliable at the moment, ongoing and future research focuses on incorporating additional pre-processing and augmentation techniques, ensemble methods and regression techniques for the bounding boxes to increase the detection accuracy and reliability of the algorithm.

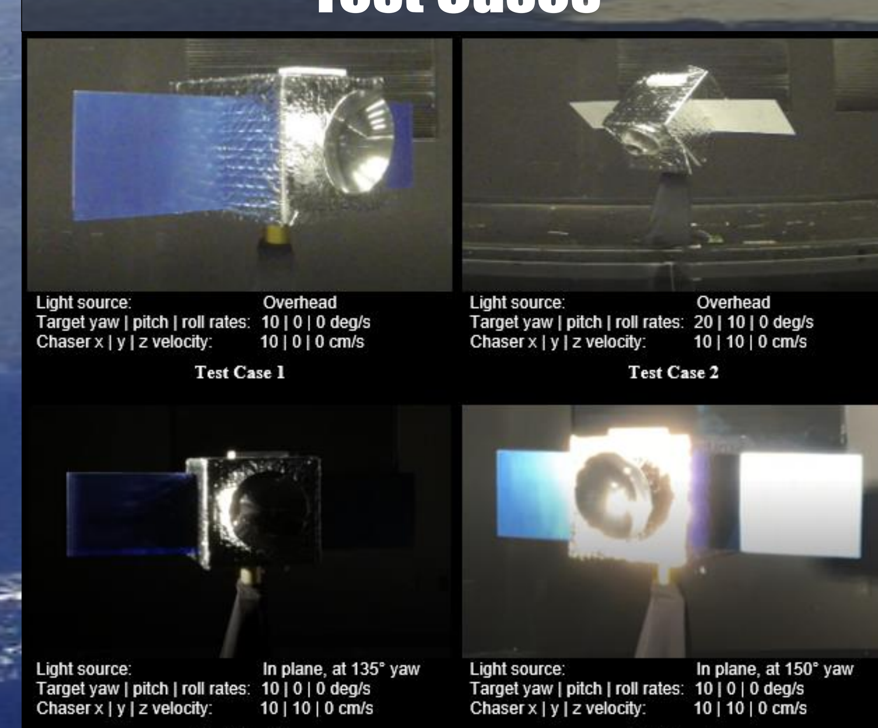
Training Dataset

Class	#Annotations
Solar Array	1204
Thrusters	737
Antennas	692
Satellite Bodies	416

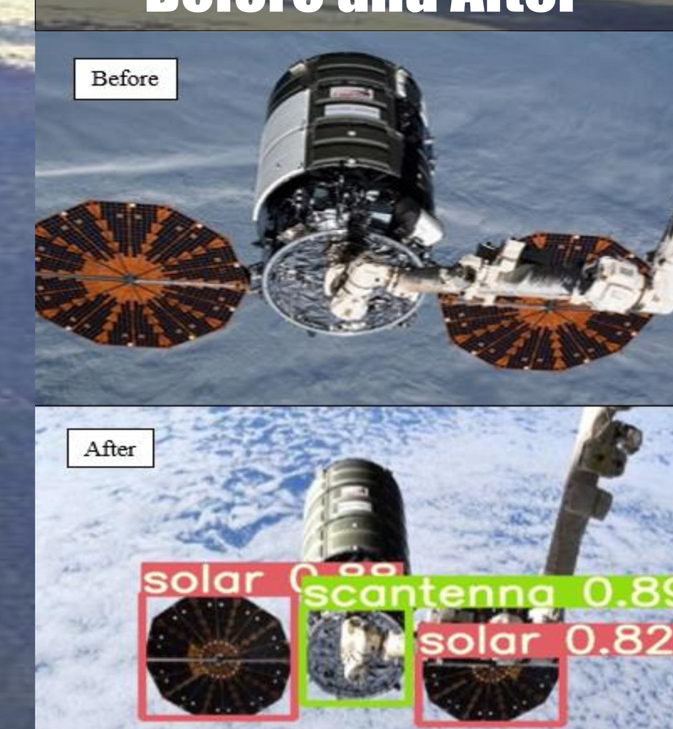
Example



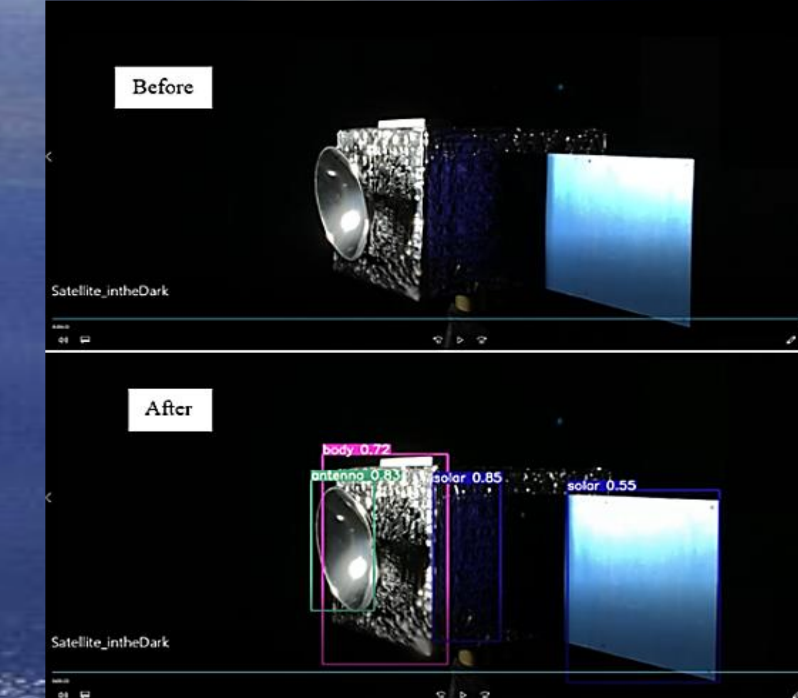
Test Cases



Before and After



Before and After



RESULTS

- Test case 3 video was chosen for result analysis since it is more complex than other cases.
- The video was inferred and analyzed every second for 37 seconds for simplicity instead of its actual rate of 140 fps. Antennas, body and solar panels showed a high false negative value which is problematic.
- However, Case 3 had the worst lighting conditions and, the training dataset chosen does not resemble the testing dataset accurately since the training dataset images are well lit and relatively easier to identify leading to a spike in the FN. Table below summarizes test results.

Error Analysis Summary of Case 3 Test Video

	Average Accuracy	Actual	YOLO Detections	FN	FP
Thrusters	1.10%	16	1	0	0
Antennas	52%	19	35	8	10
Body	52%	37	28	9	1
Solar Panels	62.90%	42	32	9	2

Since the algorithm is not completely reliable at the moment, ongoing and future research focuses on incorporating additional pre-processing and augmentation techniques, ensemble methods and regression techniques for the bounding boxes to increase the detection accuracy and reliability of the algorithm.

ACKNOWLEDGEMENT

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SOURCES: [1] M. Wilde, B. Kaplinger, T. Go, H. Gutierrez and D. Kirk, "ORION: A Simulation Environment for Spacecraft Formation Flight, Capture, and Orbital Robotics," in *Proceedings of the 2016 IEEE Aerospace Conference*, Big Sky, MT, 2016.
[2] G. Jocher, A. Stoken, J. Borovec, A. Chaurasia, L. Changyu, V. Abhiram, A. Hogan, A. Wang, J. Hajek, L. Diaconu, Y. Kwon, Y. Defretin, A. Lohia, B. Milanko, B. Fineran, D. Khromov, D. Yiwei and F. Ingham, *ultralytics/yolov5: v5.0 - YOLOv5-P6 1280 models, AWS, Supervise.ly and YouTube integrations*, Zenodo, 2021.