

and Neural Networks with Bluetooth-Enabled Inertial Measurement Unit **Imaging** | Alysia Iglesias<sup>1</sup>, Daniel Ji<sup>1</sup>, Eden Tessema<sup>1,2</sup>, Jonathan Wapman<sup>1</sup> **Telemetry** | Nien Dobui<sup>1</sup>, Samira Mohammadikashani<sup>2</sup>, Itai Ofir<sup>1,2</sup>, Abha Pandey<sup>1</sup><sub>1</sub><sub>Department of Electrical Engineering</sub> Supervisors: Dr. Rajeevan Amirtharajah<sup>1</sup>, Connie Duong (PhD student)<sup>1</sup> <sup>2</sup> Department of Computer Engineering

## Abstract

The Rocket Imaging Payload system provides a fast, accurate, and reliable method to identify ground-level targets while onboard a rocket. A continuous stream of images can be captured and analyzed in real-time using the NVIDIA Jetson TX1 and advanced imaging algorithms within a completely self-contained system. Onboard telemetry sensors report flight data via Bluetooth for real-time flight monitoring.

# Aerial Target Detection: How it's Used









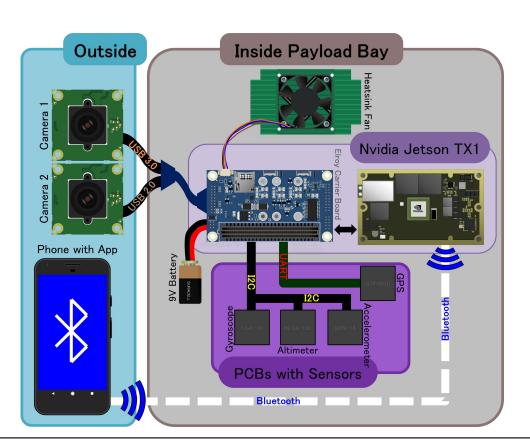


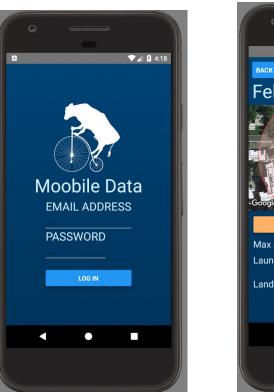


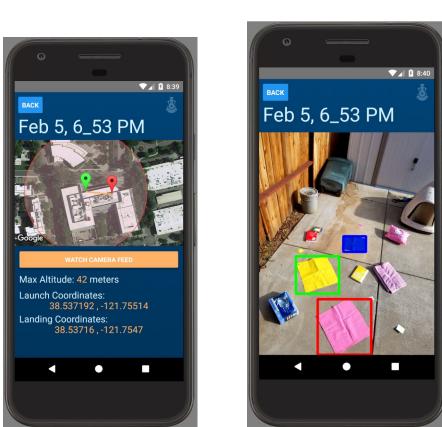
Figure 1: Aerial target detection can aid in rescue efforts, terrain scouting, reconnaissance, traffic monitoring, and many other use-cases.

# Bluetooth-Enabled Telemetry

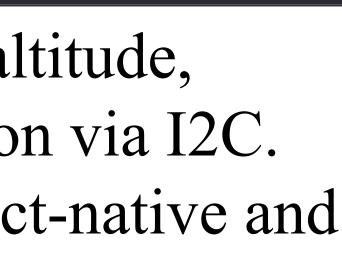
- Bluetooth-Enabled Telemetry measures altitude, angular velocity, position, and acceleration via I2C.
- Data shared via Bluetooth app using React-native and stored using Firebase.





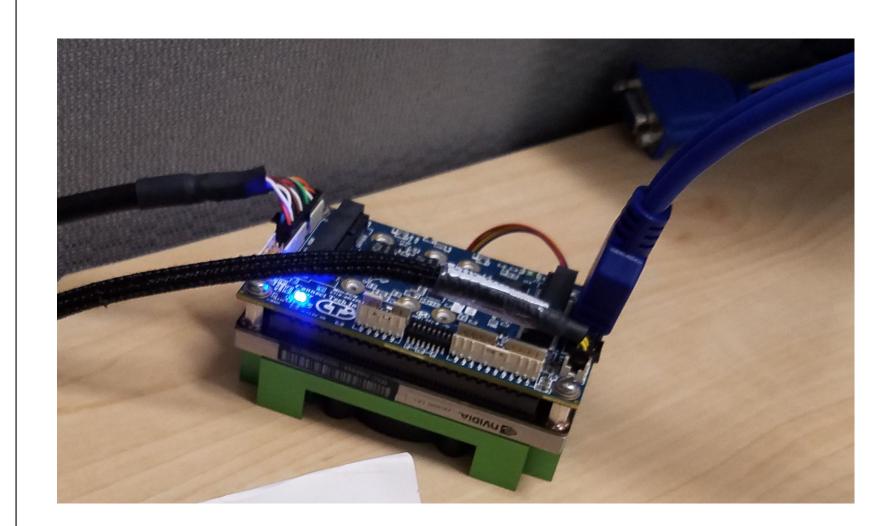


# **Rocket Imaging Payload: Identification of Ground-Based Targets using Contour Detection**



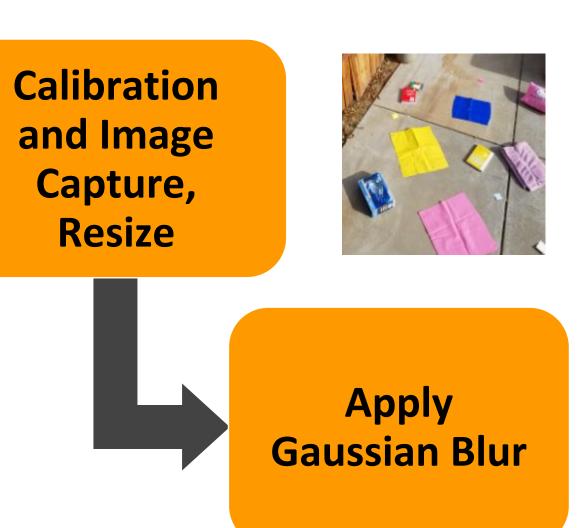
## Image Processing

- Processor: NVIDIA Jetson TX1 with 256 CUDA cores, quad-core ARM Cortex-A57 Imagers: Two USB 3.0/2.0 cameras, up to 30 FPS and 1920x1080 resolution
- Carrier: ConnectTech Elroy, I2C/USB/UART

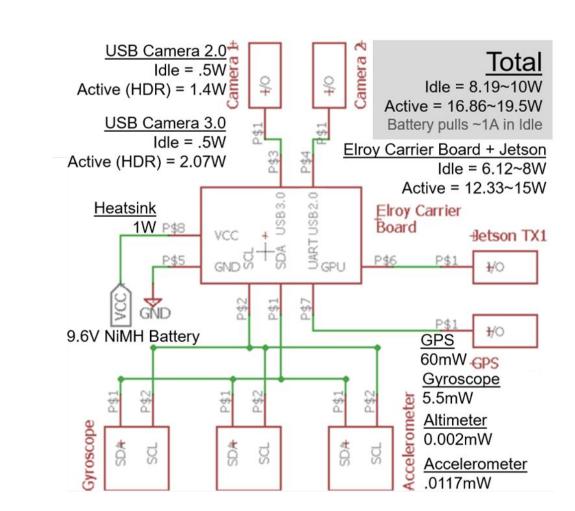


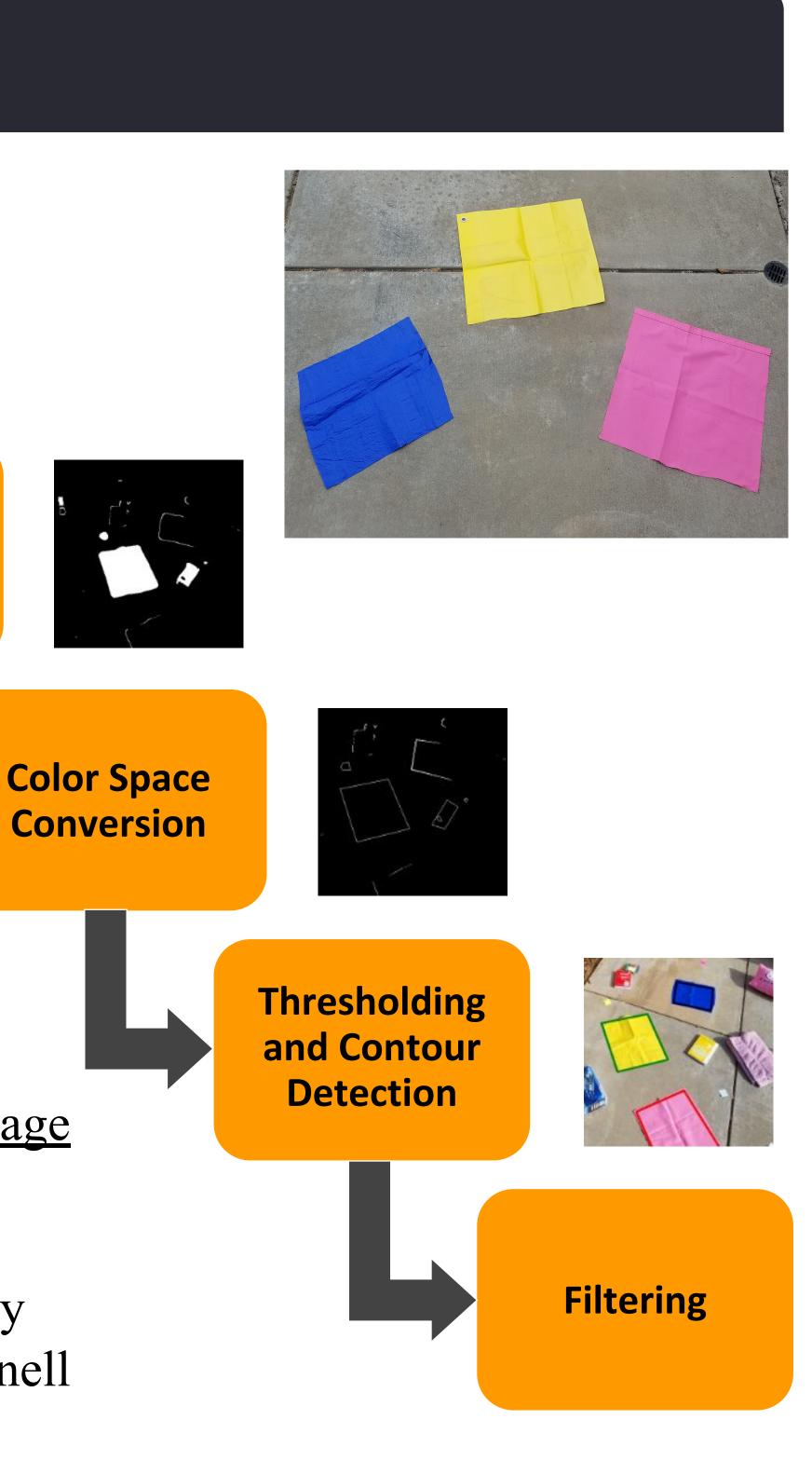
## **Figure 2: Hardware setup and schematic.**

Methods



Partially pre-trained neural <u>network as an alternative image</u> processing solution: Yolov2 ("You only look once") object-detection algorithm by Redmon and Farhadi of Cornell University [1]





## Results





Figure 3: Sampling of pre- and post-processed images after the contour detection algorithm is run. Samples include: (a) Close-up (with off-screen target and varied lighting), (b) Large distance ~60 ft. (with off-screen target), (c) Midrange ~20 ft. (with varied lighting), (d) Confusing objects (with one missing target)

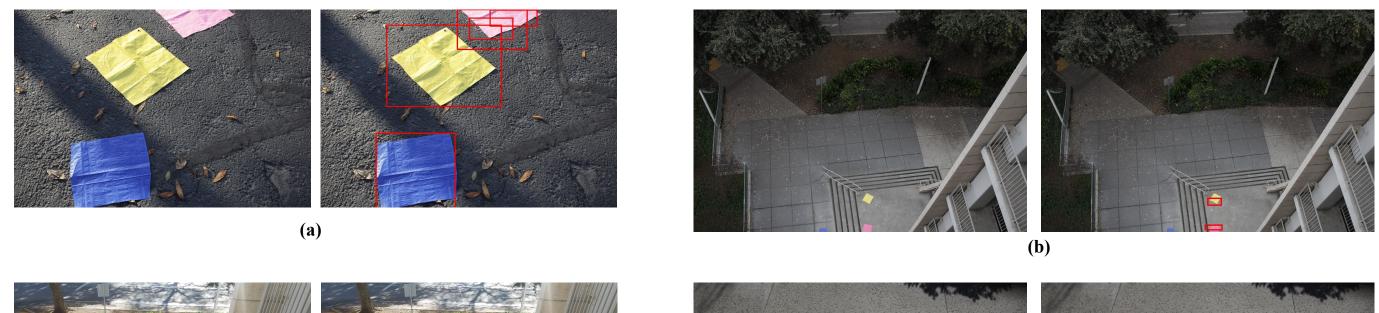




Figure 4: Sampling of pre- and post-processed images after the Yolov2 neural network is run. Samples include: (a) Close-up (with off-screen target and varied lighting), (b) Large distance ~60 ft. (with off-screen target), (c) Midrange ~20 ft. (with varied lighting), (d) Confusing objects (with one missing target)

# Conclusion

The major weaknesses of the contour detection algorithm are its inability to identify objects with a strong glare, difficulty adapting to varied lighting conditions, and mediocre accuracy in rejecting similarly-colored, non-tarp objects. However, at large enough distances (such as in Fig. 3b), it performs quite accurately, identifying all of the tarp targets in our large distance photo samples. Given that the payload is launched within a rocket which reaches apogee (one mile) within approximately 30 seconds, this ability to detect targets accurately at large distances is highly favorable, making the contour detection solution an excellent candidate for aerial target detection.

In comparison, the Yolo v2 neural network is very effective at identifying targets in difficult lighting conditions, provided that the tarps are a relatively large size in the image, such as in Fig. 4a and 4c. However, the algorithm loses accuracy when the tarps are viewed from a high altitude and thus appear very small in the image, as in Fig. 4b. Additionally, the neural network is much slower than contour detection. It is estimated to be able to reach, at most, 10 fps on the NVIDIA TX1.

Thus, for general purposes of aerial target detection, contour detection should be sufficient for identifying targets at large distances. However, the neural network's weaknesses can still be overcome. One possible workaround is to use the slower neural network for the initial object detection while the rocket is at a relatively low altitude with the tarps appearing relatively large in the image frame, and then switch to the faster, more accurate contour detection as the rocket's altitude increases.



[1] AlexeyAB, darknet, https://github.com/AlexeyAB/darknet







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