Automatic Target Recognition & Map Generation

Team: **Target Acquired**

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Team members and responsibilities

- Project Lead (responsible for communicating deadlines, arranging and leading discussions in meetings, etc.): **Justin Campbell**
- Communications Co-Leads (responsible for establishing points of contact and communicating with faculty, supervisors, and customers): **Preston Hart, Rohan Wariyar**
- Technical Co-Leads (responsible for guiding the team through technical decisions using literature and technical documentation): **Nicholas Aufiero, Ryan Ylagan**

Problem Statement

- Through reports of flooding in low-lying residential areas in Austin supplied to the Austin Fire Department (AFD), the AFD has issued a contract for the development of an Unmanned Aircraft System (UAS) for search and rescue operations to assist people stranded on roof tops surrounded by water

- Ultimately, the data that the UAS collects during flyover of critical areas will be used to deploy first aid packages as necessary to targets of interest (TOI)

- The software prototype will then use the TOI data to automatically generate a map of the affected area, return to the base/launch site, and then deliver the map with TOI locations, field imagery, and telemetry to the AFD

- The AFD will then use the features of the map to send search and rescue personnel to the proper locations

Project Objectives

- Use automatic target recognition to identify potential targets and categorize them as either a critical or non-critical target.
- Generate a map that identifies the critical and non-critical targets for the use of the Austin Fire Department.
- Implement hardware with software that is integratable with the Aircraft Design II team's Pixhawk autopilot
- Target recognition will have to be achieved at altitudes greater than 200 ft
- Iterate the design to arrive at a prototype that minimizes and automates TOI identification, map generation, and search and rescue efforts (goal: <40 minutes)

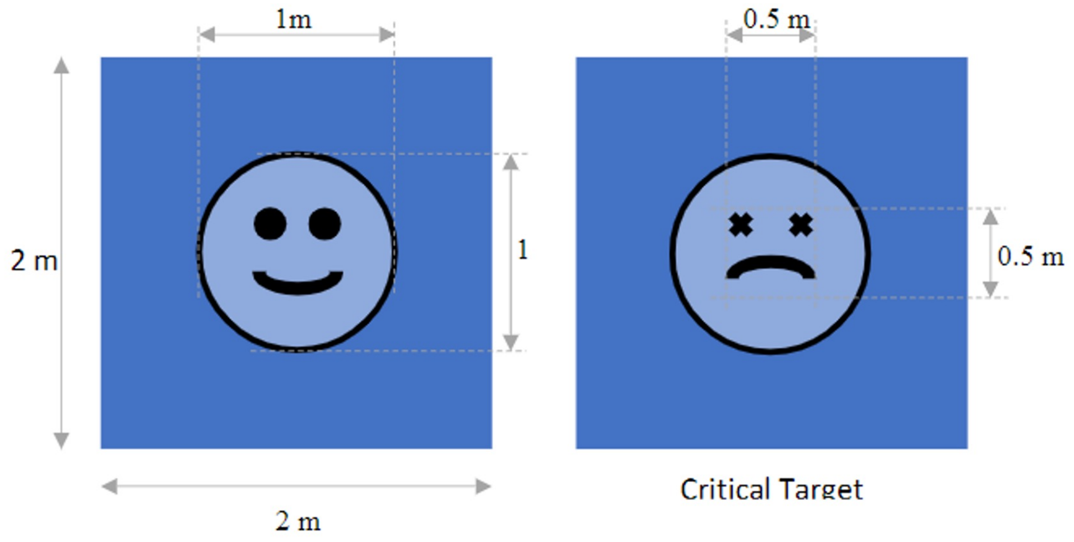


Figure: Image displaying Targets of Interest and their respective measurements. The candidate target (CAT) is displayed on the left, and the critical target (CRT) on the right.

Literature Review

Five Subject Areas we wanted to touch on:

- Machine Learning for target recognition
- ATR/Map Generation in another field?
- Integrating the co-processor with the Pixhawk Autopilot
- What problems may we encounter with this project?
- What improvements have been made to cameras/sensors?

Background of Machine Learning Image Classification Techniques

- What is Machine Learning?

  - The development and use of algorithms that are able to learn and adapt to input and output data autonomously using statistical concepts to obtain patterns from, and draw inferences about, data

- Supervised Machine Learning - an algorithm is trained using training data (typically images) to model relationships and dependencies between the target prediction output and the input features.

  - Classification
  - Regression

- Unsupervised Machine Learning - an algorithm is trained to identify patterns with unlabelled training data where there are no target variables

  - Clustering
  - Association

- Semi-Supervised Machine Learning - an algorithm operates on training data that is unlabelled at a high level, but whose data carries intrinsically important information about different features in the dataset.

  - Classification
  - Clustering

Application of Machine Learning to Automated Target Recognition (ATR)

- **What machine learning models will our team consider using for our application of ATR?**
  - Under the conditions that it is practical to use machine learning to achieve our end goal (reasonable learning curve, inexpensive, etc.) of automated target recognition, the most ideal models would be supervised or semi-supervised models.

- **In the real-world, there are many obstacles and deviations from ideal conditions that a machine learning model would need to account for:**
  - Variation in Atmospheric Properties
  - Orientation and Kinematics of Unmanned Aircraft System
  - Sensitivity and Reliability of Instrumentation

- In conclusion, developing training images and using them to account for a wide array of deviations from ideal features of the TOI’s would be necessary for a successful model

Is the idea being currently implemented in another field?

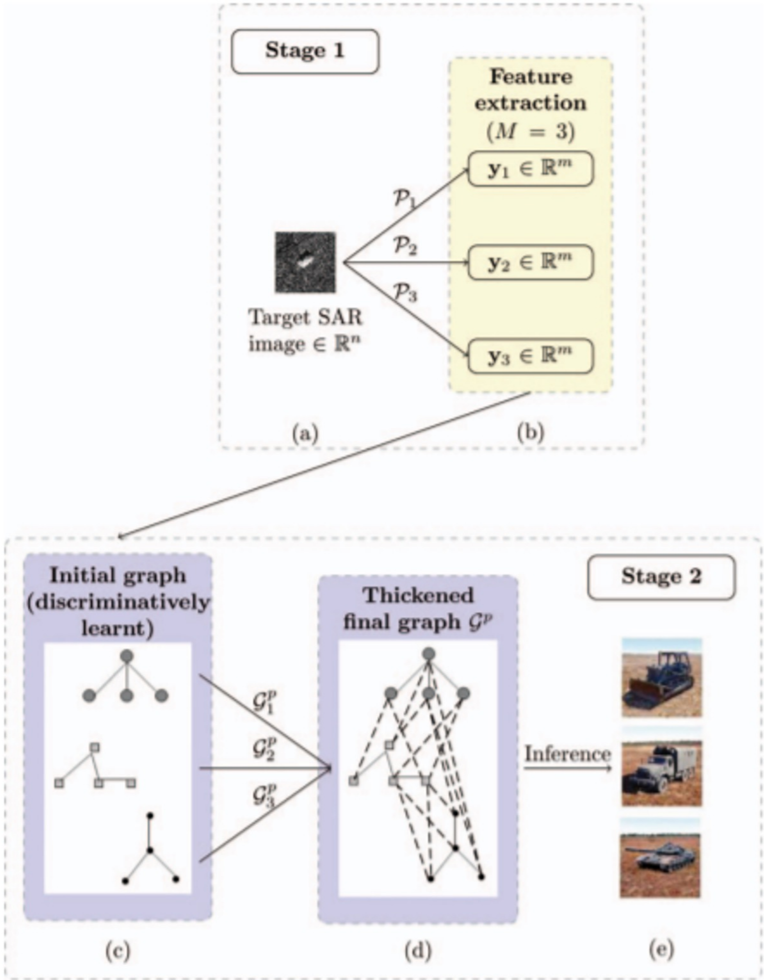
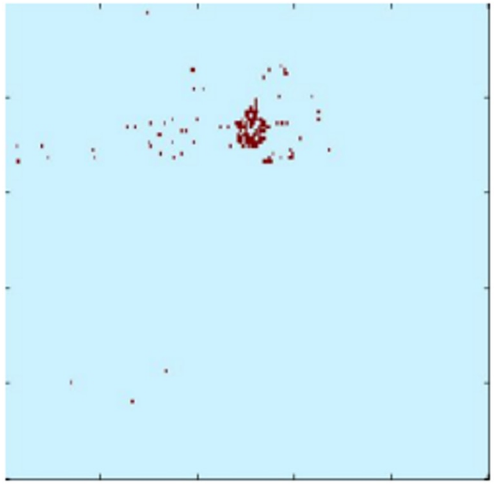


Figure 1. (A) Sample target image, (B) Feature extraction via projections P_i, (C) Initial sparse graph, (D) Final thickened graph; newly learned edges represented by dashed lines, (E) Graph-based inference

A



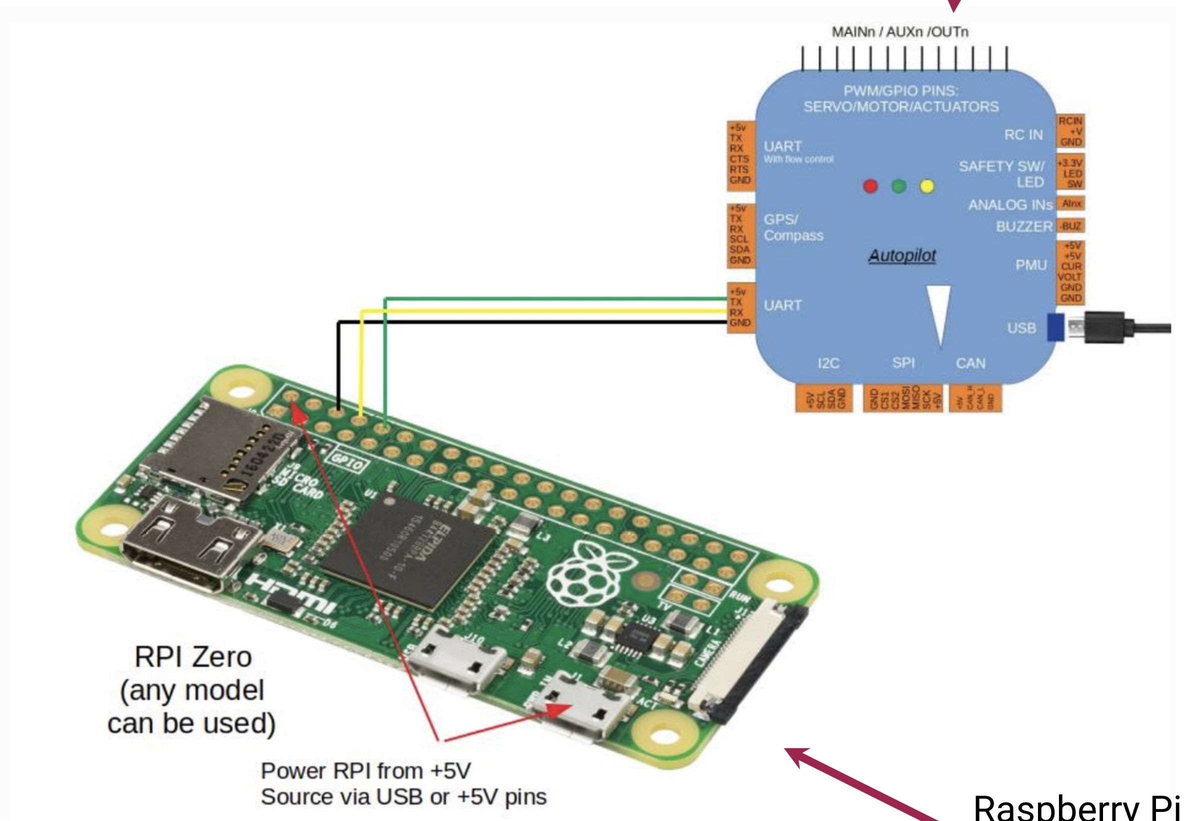
B

Figure 2. (A) Class “human” (dark tones) is weakly separable from background. (B) Scene anomaly recognized “human”, using DDM.

Integrating a co-processor with the Pixhawk Autopilot

- Why do we need a co-processor?
- How do we integrate the co-processor?
- How do we communicate with the co-processor?

Autopilot



Raspberry Pi
Coprocessor

What problems may we encounter with this project?

Four major factors that may affect our geolocation accuracy when using target recognition software as outlined in “Improving UAV-Based Target Accuracy through Automatic Camera Parameter Discovery” published by Fabian et al:

- Lens Distortion
- Timing
- Multiple Detections
- Camera Angle Calibrations

What are some mitigating strategies we could employ?

What effects do these strategies have on the accuracy of image geolocation?

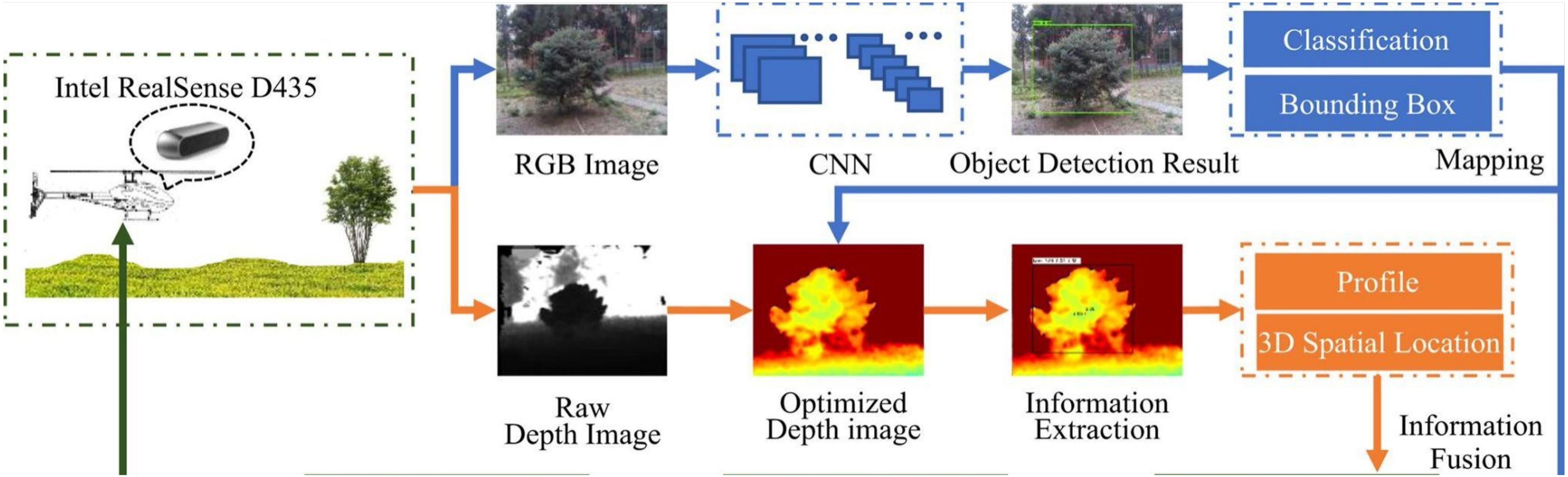
Aircraft	Uncalibrated Accuracy	Calibrated Accuracy	Improvement
Skyhunter #5	20.34	10.00	103%
Skyhunter #6	29.90	11.22	129%

Figure 1: Results of test flight that collected 200 images that were fed into the calibration solver. Geolocation accuracy saw more than a 100% accuracy improvement than before the calibration on both tests.

Aircraft	Uncalibrated StdDev	Calibrated StdDev	Improvement
Skyhunter #4	18.005	18.10886	-0.575%

Figure 2: Results after sending a large set of images through the Lens Distortion calibration. Little to no actual improvement was measured as the camera used did not have significant distortion in the first place.

Depth Cameras and Specific Applications



Enhanced location of data points

Higher altitude success

Ability to feed in more data

References

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Contribution

All team members contributed equally to the work in this presentation