Individual Identification of Zebras with Autonomous UAV Swarms

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Background

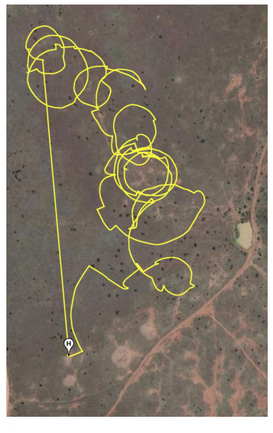
- Collecting census information about the population sizes of endangered species is an important component of conservation efforts
- Gathering individual identifying photos of animals is a time consuming and manual process
- Unmanned aerial vehicles (UAVs) piloted autonomously are well-suited to capture identifying photos due to their speed and vantage point reduces the obfuscation of vegetation

Overview

The aim of the project is to build an end-to-end pipeline to individually identify zebras from images captured by UAVs.

1. Simulation environment is built using data collected from real-world flights
2. UAV is programmed to carry out missions to capture individual identification photos of zebras
3. Navigation model is tested and refined in the simulation environment, with the goal of iteratively adding more complex capabilities, such as behavior-adaptive flight.

Data

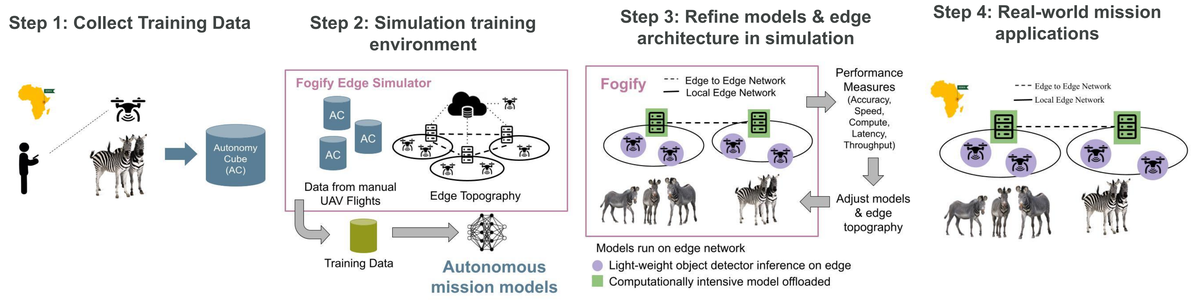


Two male Grevy's zebras, 19 minute flight, captured 1/18/23 12:47 PM

The data was collected at the Mpala Research Center in Kenya in January 2023. Video footage of Grevy's zebras, Plains zebras, and reticulated giraffes were captured using a DJI Air S2 drone shooting in 5.4K resolution. Over 60 missions were conducted, collecting approximately 17 hours of footage.

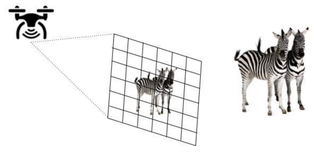
Methods

Edge Architecture for Autonomous UAV Navigation

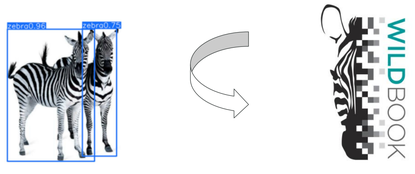


Autonomous UAV Mission for Individual Identification Photos of Zebras

Objective: Obtain photos of individual zebras of sufficient resolution to identify individuals with WildBook



1. Autonomous navigation

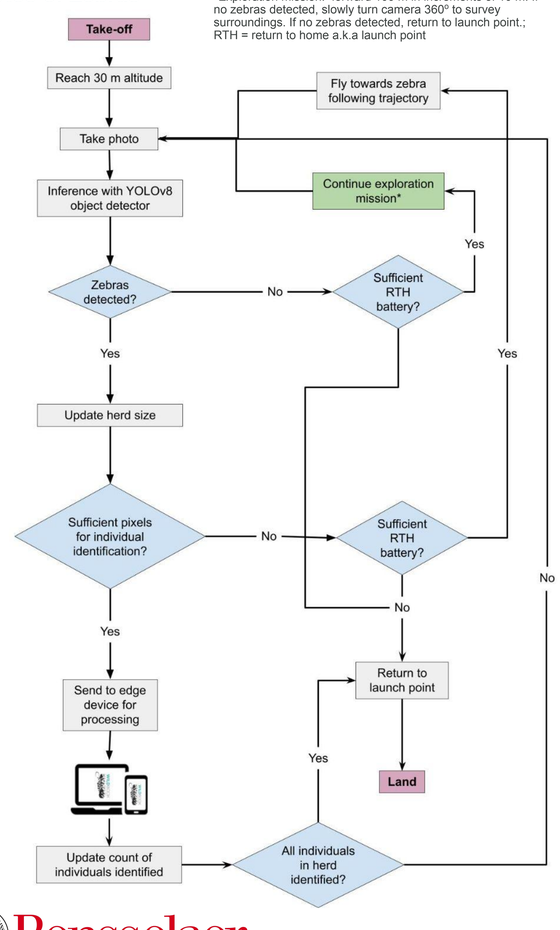


2. YOLOv8 object detector model

3. Individual Identification

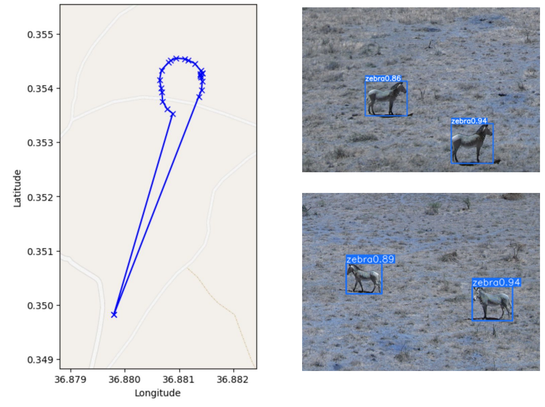
- The UAVs will be aided by a human pilot to find the animals of interest and monitor the flight for safety.
- Once the UAV takes off, it will start its exploratory phase to detect animals
- The navigation model uses a light-weight object detector model, such as YOLOv8 nano [3] to detect animals of interest and navigate close enough to capture an identifying photo (minimum 700 pixels)
- SoftwarePilot [1] is used to program the flight path for both simulated and real-world missions

*Exploration mission: forward 100 m in increments of 10 m. If no zebras detected, slowly turn camera 360° to survey surroundings. If no zebras detected, return to launch point.; RTH = return to home a.k.a launch point



Results

Using the bounding box information obtained from the object detector for navigation eliminates need for costly calculations and does not require specialized equipment, such as LiDAR. This approach reduces the amount of data transferred required, since only a few select photos that meet the required criteria will be saved to the edge device.



Simulated UAV mission for individual identification of two male Grevy's zebras

This simulated mission below took only two minutes to complete, including detecting the zebras, taking identifying photos of the two male Grevy's zebras, and returning to the landing point.

Future Work

1. Complex navigation
   - Improve the data processing pipeline to produce more complex training data
   - Add reinforcement learning component to autonomous navigation
2. Systems integration
   - Fogify simulation environment
   - Autonomous navigation model
   - WildMe for individual identification
3. Add behavior-adaptive flight to navigation policy

References

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[3] Redmon, J., & Farhadi, A. (2015). You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 779-788).

[4] W. Andrew, C. Greatwood, and T. Burghardt, "Aerial Animal Biometrics: Individual Friesian Cattle Recovery and Visual Identification via an Autonomous UAV with Onboard Deep Inference," in *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Nov. 2019, pp. 237–243. doi: 10.1109/IROS40897.2019.8968555.

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