

Introduction

Drones have exploded in popularity in both commercial and hobbyist settings, and as a result, managers of outdoor public spaces are increasingly faced with the duality of needing to allow a few drones permission to operate in support of events, while simultaneously preventing the incursion of interloping drones. Other more sensitive public facilities like prisons are also facing an increasing presence of drones, which threaten public safety when contraband like guns and cell phones are dropped into prison yards [1]. To this end, the Humans and Autonomy Lab has developed an inexpensive system that uses a microphone and Raspberry Pi with a machine learning algorithm to analyze the acoustic features of surroundings in a time series model. The algorithm generates a predictive classification which is then analyzed by a confidence algorithm to alert users through a Mobile Alerting Interface, a smartphone application.

System Design

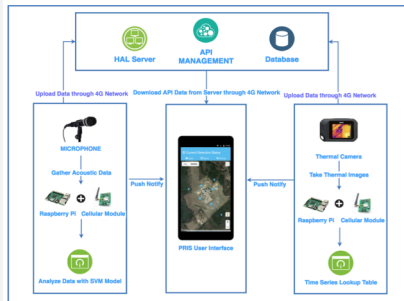


Fig. 1. Hardware System Design.

The system is an energy efficient, **low cost**, **portable**, and **versatile** device that can detect humans and identify drones (Fig. 1)

The core feature is an **Acoustic Detector** that uses an **omnidirectional microphone** and **Raspberry Pi** to process audio signals and identify drones.

The acoustic detector is also equipped with a **confidence script** based on **queuing theory** to report the confidence of detection. A **mobile API** allows the acoustic detector to send alerts to a smartphone-based **Mobile Alerting Interface (MAI, Fig. 2)** [2] with recordings to a web server for real-time or historical access.



Fig. 2. Mobile Alerting Interface (a) Detection history, (b) Geocoordinates of Detection [2].

Machine Learning Framework

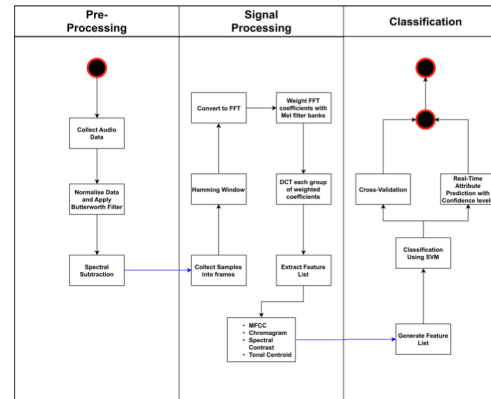


Fig. 3. Flow chart for audio signal processing & machine learning framework.

An algorithm **nu-SVM** with 3^{rd} polynomial basis function was used as a one-vs-rest classifier to categorize labels using various features (Fig. 3).

Drone sounds at **different distances** from the microphone epicenter serve as labels for the SVM (Fig. 4).

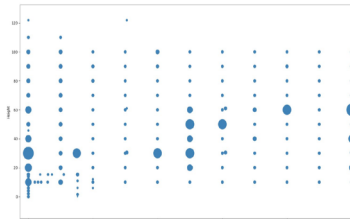


Fig. 4. Map of data distribution [3].

Results

Static (Fig. 5) and dynamic (Fig. 6) field tests with various drone models and flight characteristics were used to validate the acoustic detector.

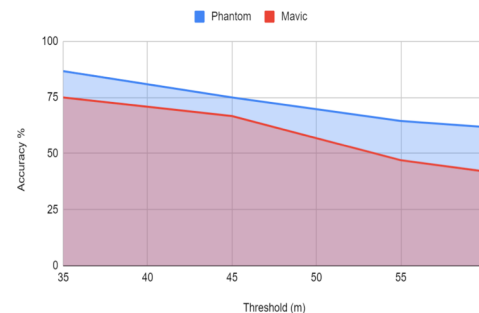


Fig. 5. Distance vs Accuracy graph for Phantom and Mavic static drone tests [3].

The system performed with **86.7% accuracy** when identifying a Phantom 4 Pro drone (a popular model in the US) within a radial distance of 35m, but dropped to 62% within a radial distance of 60m.

For dynamic tests, the system typically alerted the user at 35m for constant altitude flights, but struggled to detect descending drones. The best detection occurred at 50m for an ascending drone.

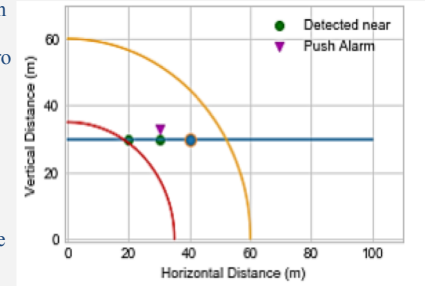


Fig. 6. For a constant altitude dynamic test flight profile, the circles denote where a detection occurred and the triangle shows where an alert occurred.

Future Work and Conclusions

- Although the current model has a decent detection rate, it was not immune to false positives, particularly by **lawn equipment**. We plan to overcome this issue by:
 - 1) Investigate the use of Convolutional Neural Nets (CNNs) which are effective in distinguishing background noises.
 - 2) Use a combination of **Radio** and **Acoustic** frequency analyzers.
 - 3) Introduce **human-in-the-loop feedback (Fig. 7)**, which will allow users to provide labels of incoming sounds through the device in Fig. 2., which will then be automatically incorporated into the model.
- With our **Clemson** collaborators, we will embed the improved system in a camouflaged setting in a public outdoor amphitheater and maximum security prison to determine more realistic detection rates.

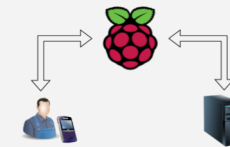


Fig. 7. A Human-in-the-loop feedback system for data labeling



Fig. 8. An artificial hawk's nest designed by Clemson collaborators to camouflage the detection device

References

- Acknowledgements to the National Science Foundation, Scotland Correctional Institution (NC), Dan River Prison Work Farm (NC), and the Town of Cary.
- [1] Khaw, C., "Drone crashes while smuggling weed into maximum security prison," The Verge, 2014. [Online].
 - [2] Wang, C., and Cummings, M., "A Mobile Alerting Interface for Drone and Human Contraband Drops," American Institute of Aeronautics and Astronautics (AIAA) Aviation and Aeronautics Forum and Exposition, Dallas, Texas, 2019.
 - [3] Mandal, S., Chen, L., Alaparthi, V., & Cummings, M.L., "Acoustic Detection of Drones through Real-time Audio Attribute Prediction," AIAA SciTech, Orlando FL, 2020.