# A Low-Cost Acoustic Alerting System for Rogue Drones in Public Spaces

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## 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 preventing the incursion of interloping drones. Other more sensitive public facilities like prisons are also facing an increasing illicit presence of drones, which threaten public safety when contraband like guns and cell phones are dropped into prison yards. To this end, we developed an inexpensive system that uses a microphone, a RF detector, and a Raspberry Pi with a machine learning algorithm to predict the likelihood of the presence of a rogue drone. This systems alerts personnel through the Mobile Alerting Interface, a smartphone application. Landscape architecture solutions were developed to camouflage the detection devices as well as to deter possible interlopers. Lastly, the trade space of variables relevant to the adoption of these systems to individual stakeholders is presented.

## System Design

Fig. 1. Hardware system installed the Koka Booth Amphitheater in Cary, NC.

The system is an energy efficient, **low cost (~$400), portable**, and **versatile** device that can identify rogue drones (Fig. 1).

The core features are an **Acoustic Detector** that uses an **omnidirectional microphone,** a **Raspberry Pi,** and an **RF (radio frequency) detector** to process signals and identify drones. The RF detector aids in reducing false alarms and has a range of 120m. If operators choose not to use the onboard drone video, the acoustic detector works as a back up with a range of approximately 60m.

A **mobile API** allows the acoustic detector to send alerts to a smartphone-based **Mobile Alerting Interface (MAI, Fig. 2) [1]** with recordings to a web server for real-time or historical access.

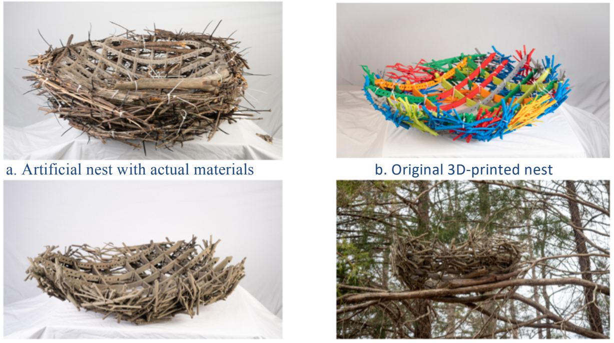

Fig. 2. Mobile Alerting Interface [1].

Table 1. Human versus CNN detection of drone sounds [2].

| Metric | CNN | Human Classification |
|---|---|---|
| Accuracy | 80% | 92.47% |
| Precision | 90.9% | 90.97% |
| Recall | 66.7% | 93.79% |
| F1 score | 76.9% | 92.36% |

In order to determine how well the system in Fig. 1 compared to human performance, a comparative experiment was conducted between humans and a convolutional neural net. With a sample of 35 participants, the human classification accuracy was 92.47% (Table 1), while the CNN accuracy was substantially lower at 80% . Most of the human misclassifications were due to a fixed wing drone aircraft, which was classified as 'not a drone'.

## Designing for Successful Integration



a. Artificial nest with actual materials

b. Original 3D-printed nest

c. Camouflaged 3D-printed nest

d. 3D-printed nest *in situ*

Fig. 3. Evolution of the design of an artificial nest in which to hide the system.

Understanding that a listening device is better suited higher up to extend its vertical and horizontal range, and that some agencies care about the look of the physical form of such a device, camouflaging the detection system in an artificial nest in one option for installation. Such a nest, modelled after a Red-tailed Hawk's nest, is common in the southeast and could accommodate a solar panel if a power source was not available.

The initial nest in Fig. 3a was very realistic as it was made of natural material and a thick plastic frame, but it was too heavy (17.6 kg ). To combat the weight and decomposition issues, we adapted the initial design to a digital format, including scanning real branches and twigs, and then printed the nest with several 3D printers. Because the design took several different printers, the initial 3D-printed nest resembled a rainbow (Fig. 3b), and then was painted with camouflage colors (Fig. 3c). The weight of the 3D-printed nest was much lighter (3.5 kg ) and could be more easily mounted higher up in a tree (Fig. 3d).

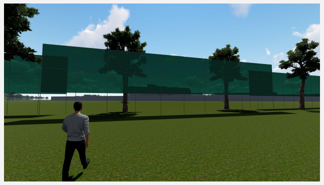


Fig. 4. Ground view of the proposed deterrence screen

One key insight is that a major source of deterrence could be making it difficult for operators of rogue drones to achieve their desired lines of sight (LOS). Instead of disrupting the top-down views from a drone onboard camera thought interventions like nets that may obscure required views, it is possible to disrupt the view of the pilot attempting to visually control a drone in flight. One natural way to block people's lines of sight in visually controlling rogue drones is to grow trees, where leaves and branches provide some protection against top-down views, and they also act as deterrent since they often present many difficult navigation challenges. Such interventions can take quite a long time to reach maturity. For those venues that want to deter rogue drone operations without the time and resources to grow trees, there is another low-cost solution. Figure 4 illustrates the use of outdoor screens as a possible cheap and flexible deterrent to such operations.

## Conclusion

Figure 5 summarizes the trade space that emerged from this effort aimed at determining what interventions could and should be designed to support high-risk venues attempting to inhibit rogue drone flights. Each venue has different needs and budgets, so the seven factors in Fig. 5 must be balanced accordingly. The most important factor to consider is the severity of intrusion, which will often drive the other second tier factors in Fig 5. For example, prisons only need these systems to work at night but need a longer range of detection because of the significantly higher consequence of an intrusion. Because of this, they may be willing to accept more false alarms than another venue.

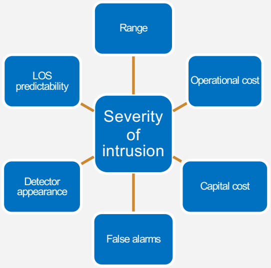



Fig. 5. Trade space for passive drone detection and mitigation. LOS = Line of Sight

## References

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[1] 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.

[2] Alaparthy, V., Mandal, S., Cummings, M, "A comparison of machine learning and human performance in the real-time acoustic detection of drones" IEEE Aerospace 2021, Big Sky Montana.