Appendix A
Brief review of the state-of-art in the field
(National & International)

An effective method of detecting and tracking drones is using an array of directional antennas and appropriate radio receivers to monitor the frequency bands normally used to exchange information between a drone and its operator. This approach works best for tele-operated drones, such as hobby drones. Nguyen et al. [1] studied various RF-based methods for identifying drones, including detecting RF reflections from propellers, eavesdropping on drone-base station communication, and analyzing movement patterns. It has also been demonstrated that changes in the RF signals caused by drone body motion may be utilized to detect and classify different types of drones [2].

Another way to identify drones is by using cameras. The detection system employed by Lai et al. [3] is a track-before-detect temporal filtering strategy. Birch and Woo [4] investigated drone detection at various wavelengths in the visible and infrared spectra. They conducted tests to detect quadcopters, octocopters, and fixed-wing UAVs, and observed that visual band inspection works best against a uniform background and detection from a distance of more than 1 km would necessitate cameras having gigapixel resolution. Rozantsev et al. [5] used a mobile ground station with a video camera covering a partial view of the sky to detect a drone heading for a collision with the ground platform. Hu et al. [6] used visible light cameras installed on a stationary ground station in a similar manner. They performed change detection and blob analysis to detect UAVs.

Muller [7] proposed a stationary camera-based system with a high-resolution visual band camera for daytime and a low-resolution short-save infra-red (SWIR) camera for nighttime detection. The system relies on acoustic signals to further improve the detection performance. Christnacher et al.[8] combined an acoustic antenna array with an active imaging system for drone detection. Their active imaging system comprises a pan and tilt camera that operates at SWIR frequencies and uses an infrared laser to illuminate the object. Shi et al. [9] developed a stationary drone detection system that combines audio, video, and RF detections via an OR operator.

In spite of the fact that drones may have a very small radar cross section, making their detection challenging, especially at long distances, various forms of radars have been employed to detect drones [10]. To identify small UAVs, Hoffman et al. [11] used a ground-based multi-static radar that uses time domain and micro-Doppler signatures. Quevedo et al. [12] used a static ubiquitous radar operating in the X band (8.75 GHz) to detect a flying drone at a range of 2 km with a resolution of 0.878 m and a probability of detection of 0.7. Instead of an active radar, Vinogradov et al. [13] used a passive one and simulated an UAV-mounted passive radar to detect adversary drones. A passive radar detects reflections of signals sent out by illuminators of opportunity (IOO). Vinogradov et al. [13] explored the use of long-term evolution (LTE) band mobile base stations as the IOO. Recently, Dogru et al. [14] proposed an anti-drone system that uses an aerial 77 GHz mm wave radar to detect drones. Morris and Hari [15] investigated the effectiveness of a mmWave automotive radar for ground-based air surveillance.

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Appendix B
Scientific Importance of the project

Driven by technological advancements and decreasing costs, the use of drones has become widespread. These days, drones are being used routinely for various tasks including aerial photography, aerial inspection, surveillance, search and rescue operations, and disaster response. In addition, drones are being used in agriculture, emergency response, and firefighting and new application fields are being explored. On the other hand, drones are also being used to breach our privacy, disrupt air travel, destroy infrastructure, and support terrorist activities. Therefore, it is imperative that effective methods to detect, track and sometimes destroy the adversary/intruding drones are developed.

In the literature, a variety of methods have been proposed for drone detection. They can be broadly classified into visual, audio, radio frequency, infrared, and radar-based approaches. Each of these approaches has its own set of advantages and disadvantages. For example, acoustic approaches recognize drone's audio fingerprint. These approaches typically require the separation of the drone's propeller sound from the background noise. High-resolution cameras (visible light as well as infrared) can also be used for the detection and tracking of drones. However, visual inspection approaches require favorable atmospheric conditions and a meaningful distance between the cameras and the drone. In addition, visual systems must distinguish between birds and drones, which is not always an easy task at a distance.

On the other hand, radar-based systems are less affected by environmental conditions and offer advantages such as localization of the target drone, including determination of its altitude. Radars have been the most popular means to detect flying vehicles. Traditional military radars are designed to identify large objects and have difficulty in detecting small drones. In addition, target discrimination may not be trivial. When the object is multiple times the wavelength, better radar detection is achieved. As a result, radars with shorter wavelengths are likely to be more effective in detecting drones. Therefore, in this project, we propose using mmWave radars mounted on swarm drones to develop an anti-drone system.

Appendix C

Methods and Procedure

This project will involve research and development activities focused on developing an anti-drone system for protecting airspace from adversary drones using a drone mounted millimeter wave radar. After the initial detection, this method ensures the target drone always remains within the follower drone's detection range. We plan to develop a prototype for demonstrating the feasibility of our approach in the real world. The tasks involved will be performed in four phases as described below:

1. Detecting Adversary Drone

Initially, we will carry out several experiments using the target and the follower drone and create a large-scale dataset of radar reflections under varying conditions. Specifically, we will consider a wide range of scenarios by varying the flight speed, altitude and the relative distance between the two drones. By leveraging our expertise in signal processing and pattern recognition, we plan to develop a data-driven machine learning (ML) algorithm that discriminates between the real target (adversary drone) and other objects in the environment from the radar data. Considering that generating comprehensive and representative training data for all possible scenarios is infeasible, we plan to explore an effective combination of a classical target detection approach and the ML model to enhance the adversary drone detection performance.

We plan to analyze the micro-Doppler (m-D) effects in the radar reflection to detect the target drone accurately. The analysis of m-D signatures of a detected target is expected to help us distinguish the target drone from radar clutter (including reflections from other airborne objects such as birds and moving trees and foliage). While the conventional time-frequency techniques generally work well, extracting the m-D signatures of the drones in flight is challenging. Therefore, we will also explore novel methods for target classification using advanced time-frequency analysis techniques for extracting m-D signatures and their subsequent classification.

Since airborne clutter can adversely affect target detection using our airborne radar, we will also consider designing approaches to detect and remove airborne clutter, resulting in enhanced detection accuracy.

2. Tracking Adversary Drone

After the initial detection of the target drone, the task is to continuously track its movement within the protected airspace. This requires determining the target drone's position, commonly referred to as dynamic states of the drone, at regular intervals. The millimeter wave radar mounted on the follower drone generates noisy information, commonly referred to as measurements, related to the relative position between the follower drone and the target drone. It may be noted that the measurements may not be directly the desired state (position), but it may be some related information. In such a situation, the desired position is called as latent state of the target drone. In that context, the tracking becomes a computational problem of determining the latent states of the target drone from noisy measurements and the computational method used for solving such a problem is known as a tracking algorithm. The tracking algorithms are applied over dynamic state space model of the drone, consisting of state dynamics and measurement equation.

The state dynamics represent the time-series variation of the latent state. Assuming that the relative acceleration of the target drone is zero, its position at any instant can be characterized by the position and velocity at the preceding instant. Therefore, we define a six-dimensional state variable , consisting of 3-dimensional axial positions and velocities at the time of arrival of the k th measurement. Subsequently, the state dynamics is formulated as follows:

$$\mathrm{X}_k = \varphi_{k-1}\left(X_{k-1}\right) + \eta_k,$$

where $\varphi_{k-1}: X_{k-1} \rightarrow X_k$ denotes a function and η_k represents the process noise. The process noise is added to compensate for various modeling errors, including the error due to the zero-acceleration assumption.

The radar on the follower drone provides noisy measurements of the distance between the two drones and the angle of sight from the follower drone to the target drone. Thus, we define a 2-dimensional measurement y_k as follows:

$$y_k = \gamma_k\left(X_k\right) + \nu_k$$

where $\gamma_k: X_k \rightarrow y_k$ denotes a function, representing the mathematical relation between the measured information and the state variables and ν_k represents the additive sensor noise.

The state-space model is nonlinear in the case of drone tracking problem [1]. Therefore, we require a nonlinear tracking algorithm, also known as a filtering algorithm in the general literature on noisy data analysis. The literature on nonlinear filtering lacks an optimal solution and practitioners rely on approximated or sub-optimal solutions. There are two popular sub-optimal nonlinear filtering methodologies: particle filtering and Gaussian filtering. The particle filtering gives better accuracy, but it is computationally very intensive. Therefore, we plan to employ Gaussian filtering for this problem. It may be noted that Gaussian filtering approximates the noises, η_k and ν_k, as white and zero-mean Gaussian. In the literature, there are a wide range of Gaussian filters with varying accuracy and computational demands. We plan to apply the cubature Kalman filter [2] due to its reasonably high accuracy with a substantially low computational demand. We may also choose to experiment with some of the more accurate filters with increased computational demands such as the cubature quadrature Kalman filter [3] and the Gauss-Hermite filter [4] if the drone tracking accuracy is not satisfactory.

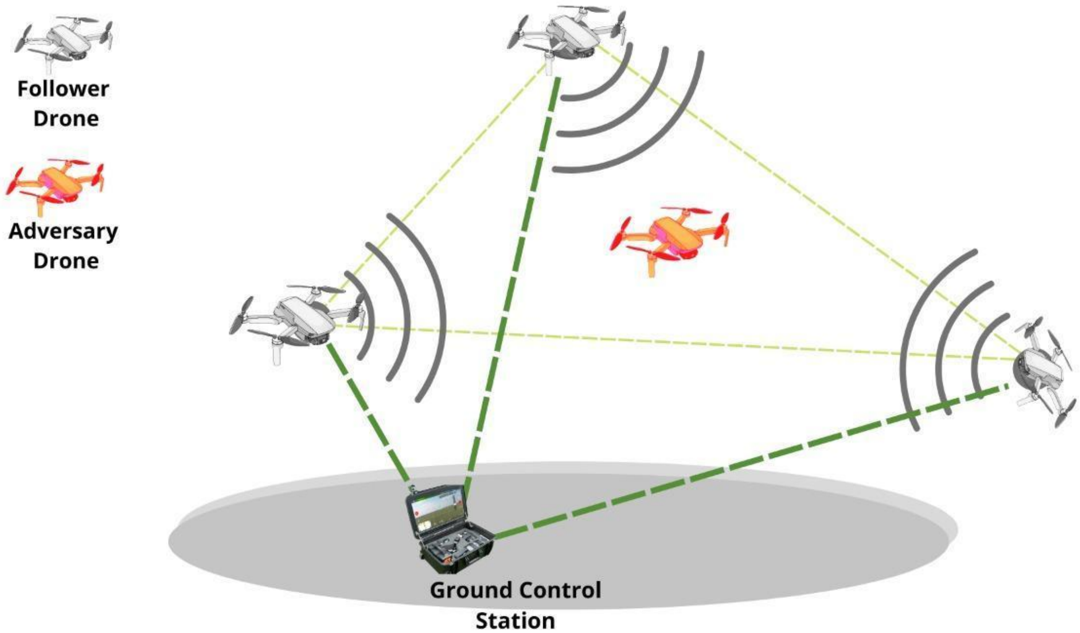
In the tracking stage, we will perform detected target discrimination using radar point cloud data to ensure that the object being tracked is a drone. We plan to explore both classical algorithms and ML models for this purpose.

3. Following Adversary Drone

In order for tracking of the detected target drone to be effective and ensure that it remains within the detection range, it is imperative that the detected drone is continuously followed. This will involve designing an appropriate control scheme to change the thrust forces generated by each of the rotors to give the desired output. In the literature, control strategies for multi-rotor UAVs have been studied extensively. The control schemes can be broadly classified into the following three categories [5]: linear robust control, non-linear control and intelligent control. The first category includes the most popular and simple proportional integral derivative control (PID). This, however, is not suitable for controlling multi-rotor UAVs having highly nonlinear dynamics. Therefore, we plan to explore a nonlinear control scheme, specifically, the backstepping control technique that has been developed for nonlinear dynamical systems. We also plan to explore intelligent controllers (e.g., neural network-based controllers) for the follower drone as these techniques have the distinct advantage that they can learn a control scheme overcoming a wide range of uncertainties. At the end of the third stage, we will conduct a proof of concept (POC) demonstration of an anti-drone system with detection, tracking and following/pursuing functionalities.

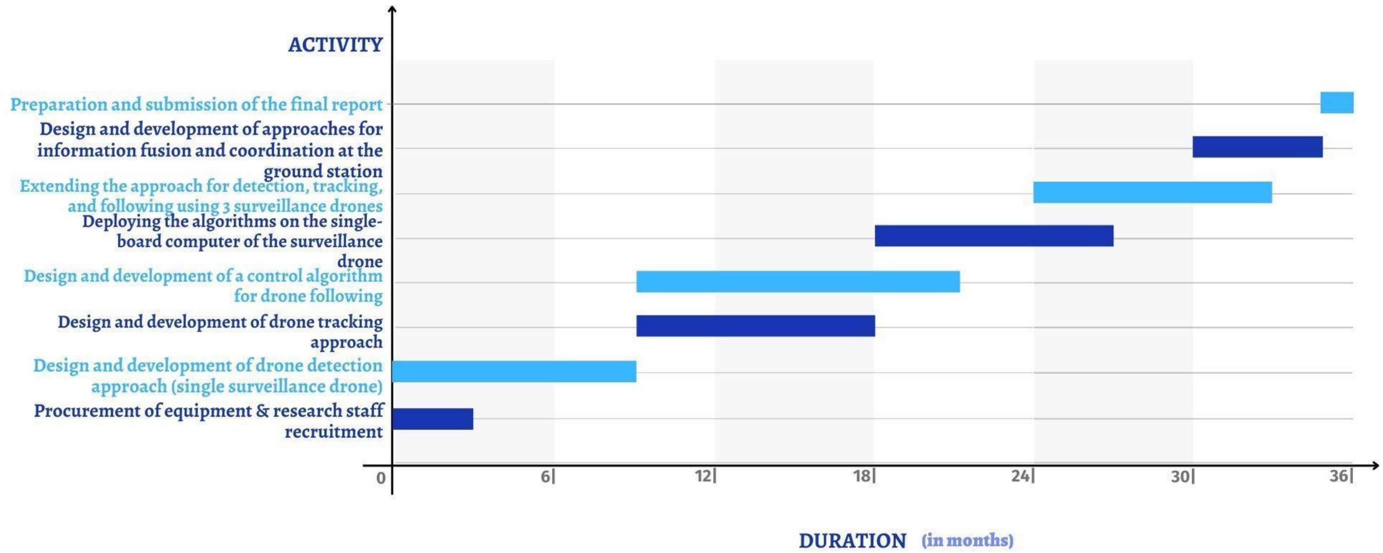
4. Extension to Surveillance using Swarm Drones

In the final phase of this project, we will focus on deploying the algorithms on the single-board computer of the surveillance drone. After deploying the algorithms on a single surveillance drone, we will extend our approach of detection, tracking, and following methods using a swam of three surveillance drones. The figure below shows a schematic diagram of the proposed approach to detecting an adversary using swarm drones.



The deployment of swarm drones for surveillance will require a control/coordination station with a display on the ground. This station will deploy swarm drones for surveillance in an optimal manner and receive information about the detection of an adversary drone from each member of the swarm. Based on the inputs received, the ground station will deploy a surveillance drone to follow the adversary drone continuously. The deployment of the swarm drones before and after the detection of an adversary drone will be formulated as an optimization problem that will be tackled using a swarm intelligence algorithm. Additionally, the ground station will act as a charging station for swarm drones based on optimal scheduling. In this project, we plan to develop a portable vehicle-based ground station that can be moved to another location in case of a change in airspace. In this phase, we will also carry out a study on the optimum number of surveillance drones that need to be deployed and their optimal separation that maximizes the detection range under relevant constraints.

Towards the end of this phase, we will also work on the other deliverables of the project, such as a technical report and high-quality publication of our research findings. phases, each with a set of specific tasks. We plan to complete the proposed project in a 36-month time frame, and the figure below shows the project timeline with different tasks/activities involved.



Technical Specifications

The surveillance drone is a 960 mm motor-to-motor hexacopter. Its frame weighs about 1050 g. We have chosen appropriate motors and propellers for the drone, i.e., TAROT 4114/320 KV brushless motor and TAROT carbon fiber propeller, so that the drone gains the required amount of thrust to fly. The total weight of the motors and the propellers is 890 g and 110 g, respectively. The flight controller, Pixhawk Cube 2.1, not only uses the data (sensor data and user command) to control the speed of the motors to make the craft move as instructed but also has the IMU sensors for extra redundancy, reducing the effect of frame vibration to state estimation. The weight of the radar used for the detection of the target drone is about 100 g. The single board computer for processing on board the follower drone weighs about 250 g. The 6S LiPo battery, which will be used to power the drone and other components mounted on it weigh about 2700 g. The camera and gimbal weigh about 550 g and 180 g, respectively. It is reported that the all up weight (AUW) can go up to 8 - 9 kgs with the above-mentioned frame, motor, and propeller combination. Based on the details provided above, the AUM of the follower drone will be around 6 - 6.5 kgs. The flight time depends on the capacity of the battery, max throttle of the motor and propeller combination, AUW of the drone, discharge capacity and power consumption by the other components on the drone. Since we will be using a 22000 mAh 6S LiPo battery, the flight time is expected to be around 40 minutes, taking all the above factors into consideration. The AWR2944 radar sensor operates in the 76-81 GHz band with an object detection range of about 200 meters. This will determine the range for the initial detection of the target drone. Using swarm drones, however, larger airspace can be protected.

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