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IECE Transactions on Intelligent Systematics
http://dx.doi.org/10.62762/TIS.2024.807714

RESEARCH ARTICLE

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Signal Strength-Based Alien Drone Detection and Containment in Indoor UAV Swarm Simulations

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Abstract

A Novel simulation framework using self-governing drones is used to locate and reduce unauthorized drones in interior environments. The recommended method uses Received Signal Strength Indicator (RSSI) to identify an alien agent drone, which has different signal characteristics than the approved swarm of UAVs. Real-time threat detection is possible with this technology. After detecting the drone, the swarm organizes itself to encircle and besiege it for 10 seconds, making it inert before returning to their original positions. This unique solution uses RSSI to quickly identify and mitigate enclosed area concerns. It provides a reliable and effective indoor drone security solution. The simulation results show that the approach works in delicate environments including warehouses, laboratories, and other indoor facilities. This study advances unmanned aerial system (UAS) autonomous swarm intelligence and security procedures.

Keywords: Autonomous Drone Swarms, RSSI, Indoor Security, Unmanned Aerial Vehicle (UAVs) and Mitigation.

Academic Editor:
Quanmin Zhu

Submitted: 13 september 2024
Accepted: 21 September 2024
Published: 23 September 2024

Vol. 1, **No.** 2, 2024.
10.62762/TIS.2024.807714

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Citation
Abro, G., E., M., Ali, Z., A. & Abdallah, A., M. (2024). Signal Strength-Based Alien Drone Detection and Containment in Indoor UAV Swarm Simulations. IECE Transactions on Intelligent Systematics, 1(2), 69–78.

1 Introduction

In recent years, drone technology has grown globally. Technological advances have expanded drone uses to indoor and outdoor use. These applications include security, entertainment, infrastructure inspection, rescue, and leisure [1–3]. Most of these applications require drones to operate autonomously or substantially autonomously. Autonomous drone flight requires continuous position tracking for safety and efficiency. Ground control stations or supporting equipment accurately locate the drone and send this information to its internal navigation system [4]. A single drone can do small-scale tasks, but size, sensor, and computational limits make handling large-scale missions difficult. Using numerous drones reduces mission failures, shortens operational times, and allows for multitasking [5]. They improve drone coordination, collective intelligence, and adaptation to changing environments. The Swarm design improves drone resilience and adaptability for mission requirements. A swarm of drones denotes a synchronised assembly of autonomous aerial vehicles that work in unison, exchanging data and responsibilities to accomplish a shared goal. Swarm operations are most effective when each drone can autonomously take off, do its duty, and return to base

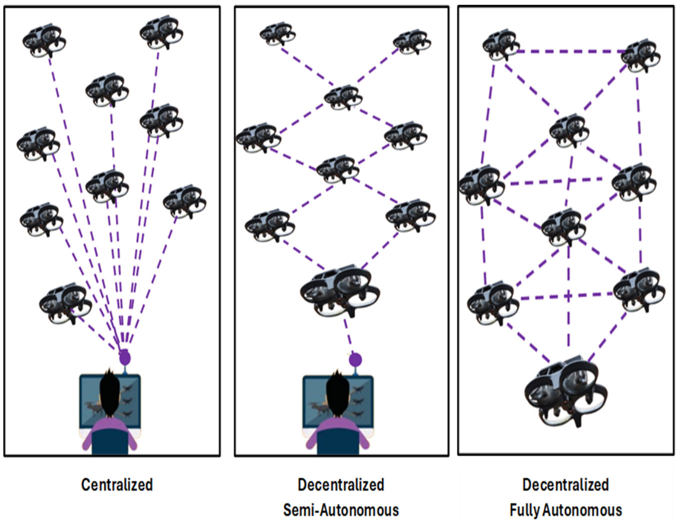

Figure 1. UAV Swarm Technology Types.

without human involvement [6].

In a swarm, drones make judgments based on information from nearby neighbors. Figure 1 displays market-available UAV swarm technology. In a centralized semi-autonomous swarm, drones depend on a central controller for decision-making, possessing restricted autonomy for local activities, hence rendering it susceptible to controller failure. A decentralized semi-autonomous swarm allocates control among drones, facilitating local decision-making and enhancing resilience, yet still necessitates external input for overarching tasks. A decentralized, completely autonomous swarm functions without human oversight, with each drone making independent, real-time decisions to guarantee dynamic task distribution, self-sufficiency, and adaptability during missions. A sophisticated control system is needed to detect an alien drone in an enclosed space. This system must be able to give accurate instructions to one agent drone and coordinate multiple agents in real time. This system uses agent-specific controllers and a central server to calculate moves and combine data [7, 8].

Outdoor, global position sensor (GPS) and inertial measurement units (IMUs) are utilized to track the drone's whereabouts. This strategy is impractical indoors and where GPS signals are lacking. Vision-based drone localization in locations without GPS signals, as shown in [9] , has significant limitations. Drone flying vibrations may degrade picture data and cause inaccurate position estimates. Vision-based methods degrade in low light or when the drone's view is blocked, reducing location accuracy. Since high-resolution cameras and real-time data processing require expensive computers, vision- based systems can be expensive to implement. Preventing accidents, processing restrictions, and faulty GPS signals make UAV movement in dynamic indoor environments harder. A quadrotor UAV autonomous control system is introduced in this work. The system uses on-board sensors and Received Signal Strength Indicator (RSSI)-based relative localization for real-time navigation, collision avoidance, and alien agent recognition without external localization equipment. A control center processes information for all drones in the swarm. This centralized control makes drone management robust. This architecture lets the system use data from all UAVs to make the best decisions and function well. When the swarm detects a hostile drone, they form a circle around it to slow it down. The study aims to improve indoor drone security through the creation of an innovative simulation framework that uses autonomous drones to identify and eliminate unauthorized or alien drone agents in enclosed spaces. The issue pertains to the escalating danger of alien drones penetrating critical indoor environments, including warehouses, laboratories, and guarded buildings. Conventional security protocols find it challenging to address the intricacies of real-time threat identification in these environments, especially with the rising presence of unmanned aerial systems (UAS). The suggested approach utilizes Received Signal Strength Indicator (RSSI) technology to identify unauthorized drones based on their signal attributes, enabling a swarm of authorized UAVs to automatically discover, encircle, and neutralize the invader. This study offers a strong security solution while enhancing swarm intelligence and autonomous drone functionalities for essential interior settings. The subsequent sections of this document are organized in the following manner. Section 2 provides an overview of the existing research on the UAV swarm. Section 3 explores the technique utilized in this investigation. Section 4 provides an exposition of the findings and analysis of the study. The paper is concluded in Section 5.

2 Related Research Work

With an emphasis on spotting possible dangers, this section examines the pertinent studies on the use of UAVs in swarm topologies for interior reconnaissance missions. The conversation is structured based on the subsequent research domains: The topics of interest discussed within this section are: (a) coordination of UAV swarms, (b) exploration in indoor environments, (c) avoiding collisions, and (d) identifying threats.

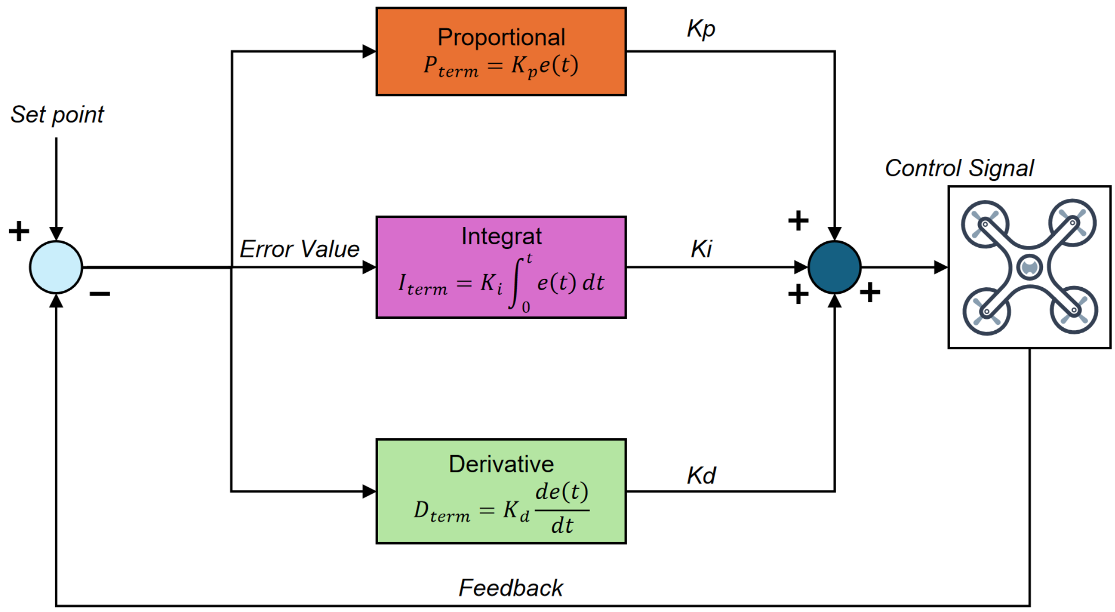

Figure 2. Block Diagram of Proportional-integral-derivative (PID) Control System.

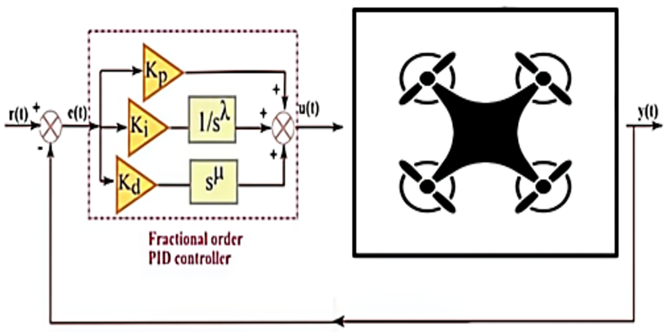

Figure 3. Block Diagram of Fractional order PID Control System.

UAV swarms are an innovative method of utilizing drone technology, where numerous drones work together and synchronize their operations to accomplish shared objectives. The utilization of this cooperative strategy provides notable benefits compared to individual drones, resulting in the rapid expansion of research in the field of UAV swarms. Recent research [10] and [11] highlight swarm drones' collaborative transportation, constructing, surveying, and search and rescue operations. Recent research has focused on velocity and location estimates for indoor and GPS-denied localization [12–14]. Vision-based algorithms and sensor fusion are prominent indoor drone localization and velocity estimation methods. Sensor fusion integrates drone sensors to make accurate estimates. IMUs, LiDAR, ultrasonic, infrared, and RSSI sensors are examples [15]. Youn et al. provide a novel navigation method for autonomous Micro Aerial Vehicles. This system uses 2D LiDAR and an RGB-D camera to correctly locate MAVs and detect obstructions. The article shows the usefulness of affordable sensors, but the RGB-D camera may struggle in low light and the LiDAR range may be limited in larger interior settings. Alizera et al. [16] use speaker-generated ultrasonic acoustic signals to properly locate and move drones inside structures. This method is cheaper than visual cue-based ones. However, noise and interference can affect these signals. Ali et al. [17] use ultra-wideband (UWB) signals to estimate indoor UAV velocity. They solve noise and interference issues. It requires a Vicon mission capture system as ground-truth, which may not be available. The proposed solution was tested experimentally. Another study [18] offers using a microphone array to assess location and velocity using acoustic inertial measurement. This method outperforms UWB-based systems. Effective collision avoidance is essential for UAV swarm safety [19]. investigates decentralized control formation, where UAVs decide autonomously [20]. Decentralized swarm navigation is suggested for difficult outdoor search and rescue missions by Horyna et al. Other studies [21] use consensus-based virtual leader tracking to steer swarms to goals while maintaining formation. Centralized control forms promote efficiency and coordination despite their complexity. A few studies [21] mention a centralized strategy where a leader UAV controls the swarm's UAV placements relative to its location. This leader alone regulates swarm behavior, formation, and environmental interactions. Another study [20, 21]

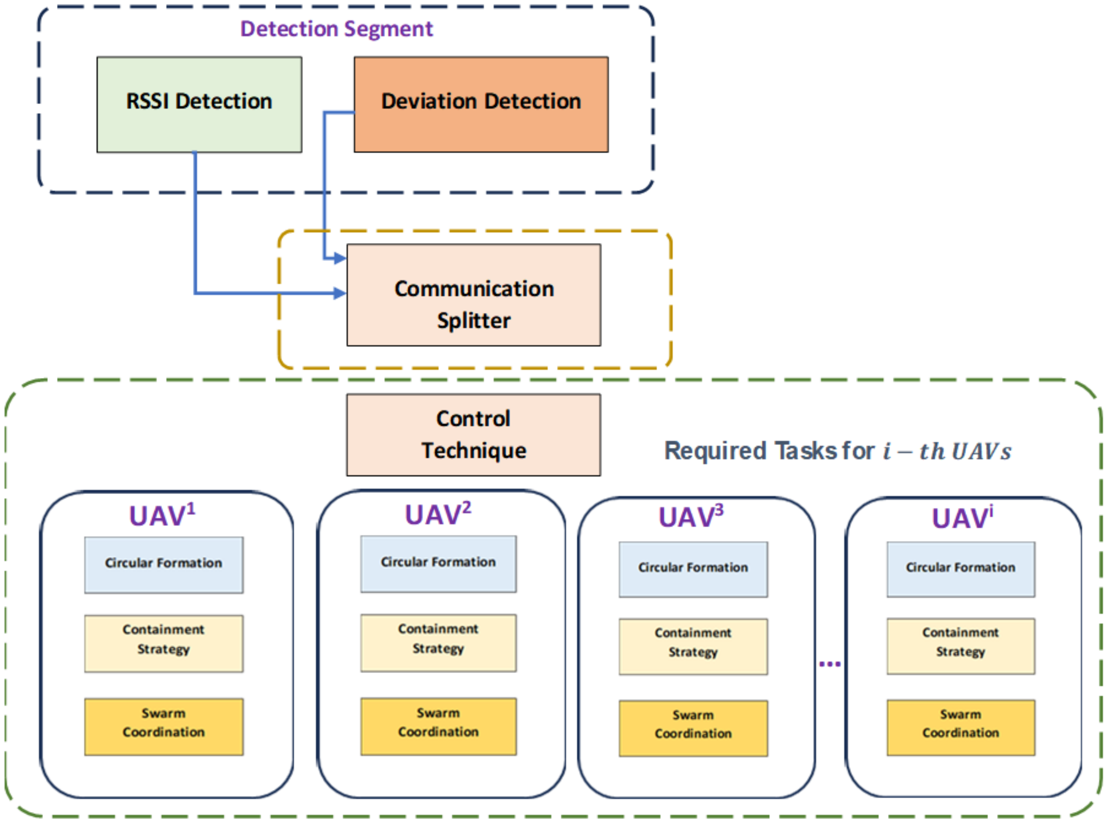

Figure 4. Block Diagram of Proposed Approach.

adds tight distance and angle thresholds to the UAV swarm leader-follower model. Machine learning and computer vision enable autonomous UAV threat detection, a well-studied topic. Based on [19], offer a framework that coordinates a swarm of "loyal wingman" drones to defend autonomously and cooperatively utilizing finite state machines, behavior trees, and control techniques. A self-organizing defense system to intercept hostile UAVs is suggested in [20]. UAV swarm coordination, indoor navigation, collision avoidance, and threat detection have improved, but combining them into an indoor swarm drone system is tough.

This study presents a Fractional Order PID (FOPID) autonomous control system to fill this gap. According to MATLAB and Simulink software simulations, the suggested system uses on-board sensors and RSSI-based localization to travel indoors effectively and detect hazards with appropriate algorithms, enabling completely autonomous UAV swarm operations for indoor threat assessment. Before one may jump to methodology section, please understand the concept of RSSI first. RSSI quantifies the power level received by a wireless device from a transmitting source, commonly employed in radio communications to denote signal strength. It assesses the strength of the signal between two devices, such as drones or wireless transmitters. RSSI values can be utilized to identify an alien drone by assessing the signal intensity from unfamiliar or unauthorized sources. As the drone approaches or retreats from the detection system, the RSSI value varies, enabling the system to approximate its distance. Utilizing a network of several detectors, triangulation methods can be applied with differing RSSI measurements to accurately determine the position of the alien drone and monitor its trajectory. This approach effectively identifies unauthorized drones or those not affiliated with a recognized network.

3 Methodology

This paper proposes an automated swarm control system that can detect and contain extraterrestrial drones based on signal strength. Proportional-Integral Derivative (PID) and Fractional Order PID (FOPID) controllers activated by RSSI values control a few UAVs in an indoor setting. Alien drones are contained using RSSI data. The suggested method uses a swarm of RSSI-equipped UAVs to measure signal strength. Each UAV may operate alone and communicate with others. The control system has two phases. The RSSI-based first stage is meant to detect alien drones. Second,

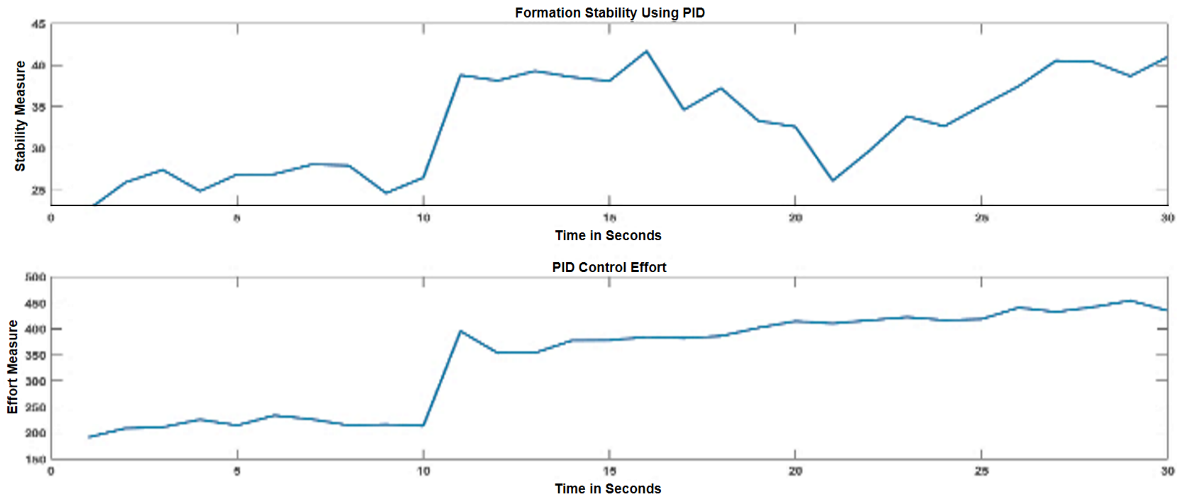

Figure 5. PID Control Effort and Stability before Alien Drone Detection.

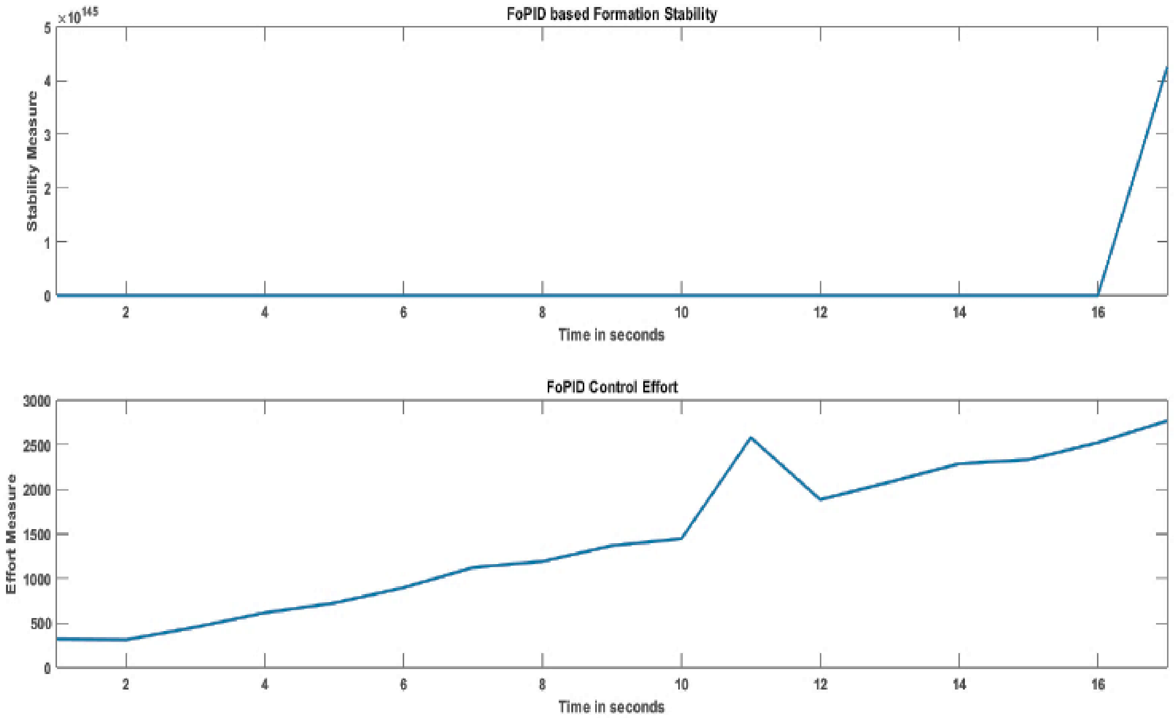

Figure 6. FOPID Control Effort and Stability before Alien Drone Detection.

implement a containment strategy using PID and FOPID controllers.

3.1 Detection Mechanism

The RSSI measurements are constantly examined to identify any deviation from the anticipated range. An alien drone is detected when the received signal strength indicator (RSSI) value of any unmanned aerial vehicle (UAV) deviates significantly from the rest of the group. Let $RSSI_i$ be the $RSSI$ value of the $i-th$ UAV. Thus, the detection criterion can be defined as:

$$|RSSI_i - RSSI_{mean}| > \Delta RSSI \qquad (1)$$

Whereas $RSSI_{mean}$ is the average $RSSI$ value of all $UAVs$ in the swarm and $\Delta RSSI$ is a predefined threshold.

3.2 Control Design

Upon detection of an alien drone, the swarm control system is activated to contain the detected drone using PID and FOPID controllers.

The Proportional Integral Derivative (PID) controller for each UAV is defined in equation (2) and the block

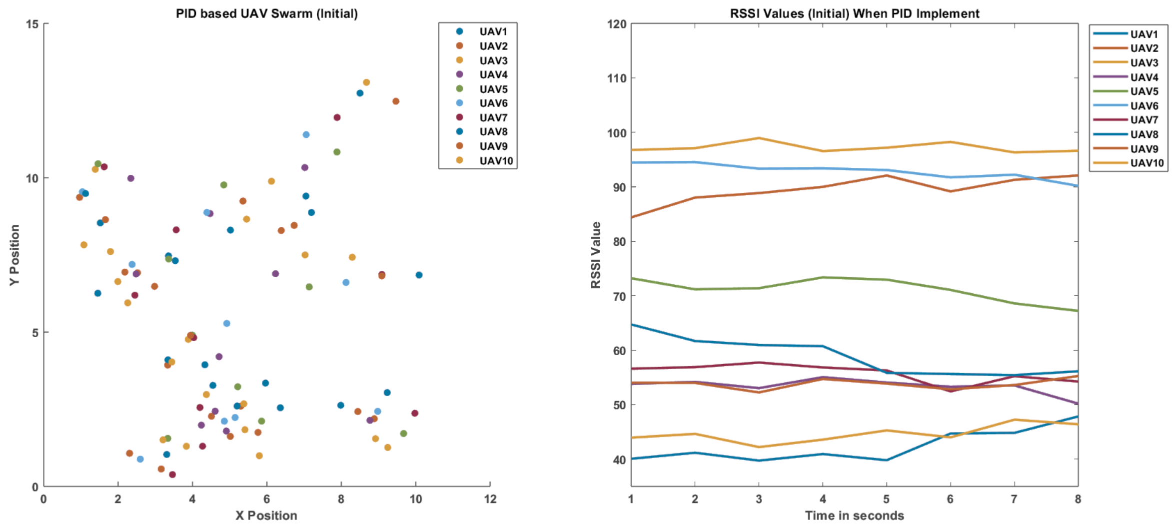

Figure 7. PID-based UAV Swarm and RSSI Values before Alien Drone Detection.

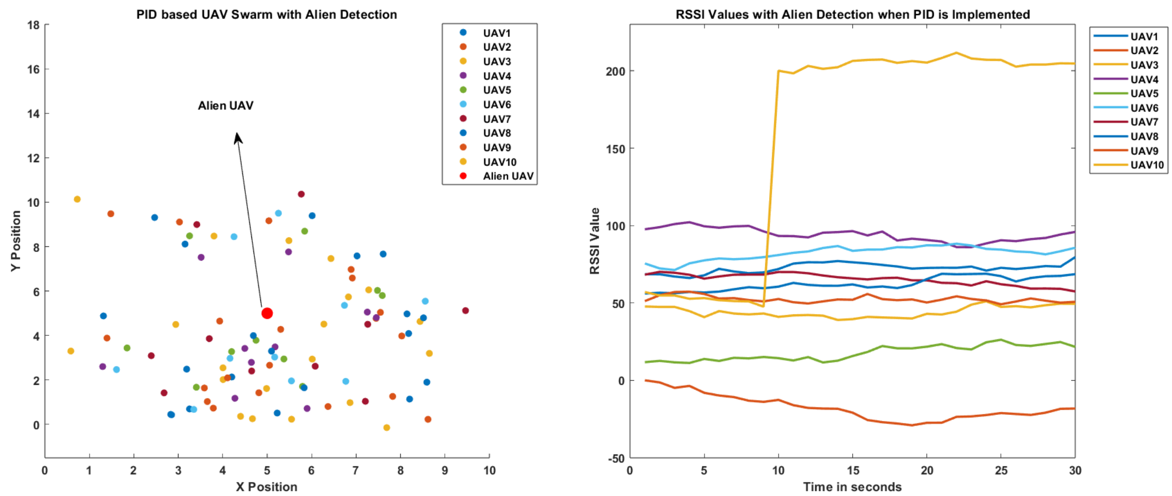

Figure 8. PID-based UAV Swarm and RSSI after Alien Drone Detection.

diagram is shown in Figure 2.

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \tag{2}$$

Whereas fractional order PID (FOPID) controller extends the PID by incorporating fractional calculus, defined as:

$$u(t) = K_p e(t) + K_i D^{-\lambda} e(t) + K_d D^{\mu} e(t) \tag{3}$$

Whereas $D^{-\lambda}$ and D^{μ} are the fractional integral and derivative operators and moreover μ and λ are known as the order of differentiator and integrator respectively. The block diagram has been shown in Figure 3.

3.3 Containment Strategy

Upon detection of an extraterrestrial drone, the implementation of the containment plan is initiated. The unmanned aerial vehicles (UAVs) adopt a circular configuration around the identified drone to constrain its mobility. The PID or FOPID controller is utilized to regulate the position of each UAV within the formation. The control input for each UAV will either be based on PID or FOPID to minimize $e_j(t)$ and maintain the circular formation. This entire methodology is shown in Figure 4.

Moreover, the desired positions for UAV in a circular formation can be computed as $x_j = x_0 + R\cos\left(\frac{2\pi j}{n}\right)$ and $y_j = y_0 + R\sin\left(\frac{2\pi j}{n}\right)$ whereas (x_0, y_0) will be the position for the alien drone, the term 'R' is the radius of the containment circle and j is known as the index of the UAV available in the circular formation. In this way the error signal for each UAV can be calculated as:

$$e_j(t) = \sqrt{(x_j(t) - x_j)^2 + (y_j(t) - y)^2} \tag{4}$$

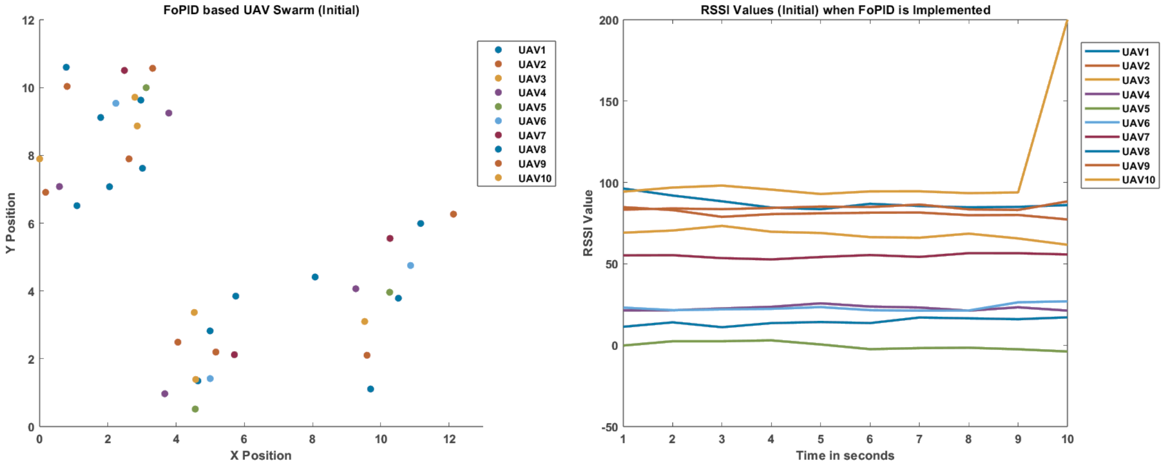

Figure 9. FoPID-based UAV Swarm and RSSI before Alien Drone Detection.

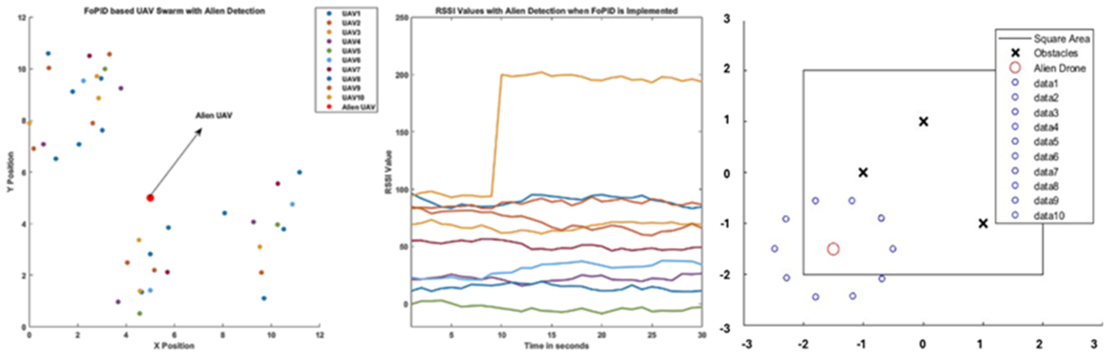

Figure 10. FoPID based UAV Swarm and RSSI Values After Alien Drone Detection & Circular Formation (Click here to see video).

4 Software Simulations

This section showcases the simulation outcomes of the autonomous swarm control system, which utilizes a PID and Fractional Order PID (FOPID) approach, to detect and confine foreign drones by analyzing RSSI values. The simulations are performed within a MATLAB environment. This study simulates a scenario in which a swarm of number of unmanned aerial vehicles (UAVs) operates within a controlled indoor environment. The UAVs are outfitted with RSSI sensors to ascertain the signal intensity emitted by other drones. The PID and FOPID controllers are activated by RSSI values to identify and confine any foreign drone within a circular arrangement. The performance of both controllers is assessed using various measures, including Detection Time, Containment Time, Formation Stability, and Control Effort. To optimize performance, PID and FOPID controller parameters are modified. The table below provides a concise summary of the parameters utilized in the simulations.

Prior to the detection of the extraterrestrial drone, Figures 5 and 6 illustrate the control effort and formation stability of the UAV swarm for PID and FOPID respectively. The control effort, quantified as the cumulative value of the absolute control signals, demonstrates how the PID or FOPID controller modifies the UAV positions to sustain the formation. The initial positions of the 10 UAVs in the PID based swarm and their corresponding RSSI values over the first 10 timesteps are visualized in Figure 6 on next page. At first, the UAVs are placed in a 10×10 area in a random manner, and their RSSI values experience minor fluctuations caused by random noise. Each drone's control algorithm uses the average RSSI.

Table 1. Optimized Parameters for PID and FOPID Control.

Parameter	Value (PID)	Value (FOPID)
K_p	1.2	1.5
K_i	0.01	0.05
K_d	0.5	0.7
λ	–	0.9
μ	–	0.8

The formation stability is quantified by calculating

Table 2. Optimized Parameters for PID and FOPID Control.

Control Strategy	Performance Metrics (in the presence of Alien Drone)					
	T_s	T_d	T_c	$RSSI_{max}$	$St_{measure}$	C_{effort}
PID	1	-	-	61.23	0.56	12.3
	2	-	-	62.11	0.54	13.2
	3	-	-	60.75	0.57	12.8
	–	–	–	–	–	–
	10	10	20	200	0.63	45.6
	11	10	20	198.5	0.60	40.7
	–	–	–	–	–	–
	30	10	20	195.2	0.55	35.2
FOPID	1	-	-	61.23	0.60	12.6
	2	-	-	62.11	0.64	13.2
	3	-	-	60.75	0.67	12.6
	–	–	–	–	–	–
	10	10	20	200	0.73	40.6
	11	10	20	198.5	0.82	45.7
	–	–	–	–	–	–
	30	10	20	195.2	0.87	45.9

Table 3. Symbols and Description.

Symbols	Description
T_s	Timestep in seconds
T_d	Detection time in seconds
T_c	Containment time in seconds
$RSSI_{max}$	Maximum Value for RSSI
$St_{measure}$	Stability measure
C_{effort}	Control Effort Measure

the standard deviation of the UAV placements, which provides a measure of how consistently the swarm maintains its formation. Figure 7 displays the locations of the PID based UAV swarm at timestep 10, following the detection of the alien drone. Additionally, it presents the RSSI values of the swarm during the whole simulation. When the alien drone is detected (identified by a notably higher RSSI value), the swarm surrounds the alien drone in a circle formation to contain it. The RSSI values depict the instance of detection and the subsequent stabilization when the UAVs adapt their positions. The simulation results for the UAV swarm control system using Fractional Order PID (FOPID) are depicted in Figures 8 and 9. Figure 8 displays the initial locations of the 10 Unmanned Aerial Vehicles (UAVs) inside a 10×10 region and their matching Received Signal Strength Indicator (RSSI) values during the first 10-time intervals.

The Unmanned Aerial Vehicles (UAVs) are initially distributed in a random manner, and their Received Signal Strength Indicator (RSSI) values experience modest fluctuations because of noise. Figure 10 illustrates the positions of the UAVs and the RSSI values during the whole simulation, with a specific focus on the detection of the alien drone at timestep 10. The alien drone, which has a notably elevated RSSI value, prompts the swarm to assemble in a circular formation to enclose it. The RSSI values indicate the occurrence of this detection event and the following stabilization when the UAVs modify their positions.

The formation stability, as indicated by the standard deviation of UAV placements, first declines because of the rapid maneuver. However, it subsequently stabilizes once the containment is achieved, so showcasing the efficacy of the FOPID control system in both preserving the formation and adjusting to new demands. Whereas the control effort, quantified as the cumulative value of the absolute control signals, demonstrates how the FOPID controller modifies the UAV positions in order to sustain the formation in figure 10. Whereas the comparative analysis in terms of time step, detection time, containment time, maximum RSSI values, stability measure and control effort has been summarized in Table 2.

5 Conclusion

The comparative analysis of PID and FOPID control algorithms for UAV swarm management reveals FOPID's distinct superiority in stability and confinement precision. Both systems successfully identify and contain the alien drone; however, FOPID demonstrates markedly superior stability metrics, achieving a score of 0.87 by timestep 30, in contrast to PID's 0.55. Although it necessitates increased control effort, reaching a maximum of 45.9, FOPID guarantees enhanced precision and stability in swarm control, rendering it the superior option for applications that require high reliability and robust performance in dynamic settings. Its improved stability and precision establish FOPID as the optimal approach for preserving swarm integrity and addressing anomalies, providing a significant advantage over PID in advanced UAV swarm operations.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgement

The authors express gratitude for the assistance rendered by the Interdisciplinary Research Centre (IRC) for Aviation and Space Exploration at King Fahd University of Petroleum and Minerals (KFUPM) in advancing this research. The project is financed by IRC for Aviation and Space Exploration as part of an internally sponsored initiative under the cost centre INAE2408.

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