A Novel Swarm Defense End-to-End System for Autonomous Drone Detection, Tracking, and Neutralization

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ABSTRACT

As the usage of drones across various applications continues to grow, the security challenges associated with their unsanctioned operations in restricted zones become increasingly critical. To address these challenges, we present a novel approach for automatic and autonomous threat management that detects drone intrusions and executes real-time countermeasures. The proposed system, called BlueSwarm integrates sensor data, implements data communication among resources, and leverages artificial intelligence to operate a counter-attacking swarm of drones. This work was validated during simulated and real-world experiments, confirming its detection, tracking and neutralization capabilities.

The proposed counter-UAV system integrates a ground segment and an air segment. The ground segment is composed of a ground control station, manned by an operator and acting as a Command & Control Center, alongside a ground radar and a PTZ camera for long-range detection, classification and localization of incoming threats. The air segment is composed of a fleet of five drones, each embedding an Electro-Optic sensor and a deployable net as neutralization payload. Those drones deploy autonomously as a swarm to intercept, track, assess and neutralize the intruding drones while keeping the human operator in the loop. Each drone is operated by its own AI agent working collaboratively with the others and with the human operator. The system is designed for scalability and adaptability. The number of ground sensors, their type and distribution in space can be adjusted depending on the needs and configuration of the space to protect. The number of defending drones and their payloads can be equally adapted. The system relies on machine learning techniques to detect, track and localize intruders, and to adapt to constantly evolving threats.

We have studied, designed and implemented, in collaboration with subject matter experts, different use cases to test our system in simulation and during real-world demonstrations. Those use cases involve the intrusion of up to five enemy drones exhibiting patterns of careless, clueless and criminal operators, evolving as independent individuals or in swarm in simulations, and two enemy drones for real-world demonstrations.

Each mission is organized in four distinct phases, ensuring a streamlined and efficient process from detection to neutralization: (i) ground sensor-based detection, classification and localization of potential threats, (ii) deployment of the defensive swarm of drones, (iii) assignment of each drone to individual *targets, and (iv) tracking and neutralization of the invading drones, combining ground and embedded sensors. During a mission, the airspace is divided into specific zones. First, a delimited protected area where any unauthorized drone activity is strictly forbidden. Secondly, a buffer area where any intrusion triggers a reaction from our system, allowing for a coordinated response before reaching the protected area.*

Our research contributes to the advancement of security measures against the escalating drone threats by providing a comprehensive, adaptable and scalable solution enabling collaborative autonomy thanks to relevant technologies and procedures. By combining our new components and existing system, we aim to mitigate risks and safeguard restricted areas against unauthorized drone activities. Developed in collaboration with subject matter experts, the research contributes to the advancement of counter-UAV technologies within the NATO S&T community.

1.0 INTRODUCTION

Driven by rapid technological advancements and widespread accessibility, drones now represent a significant security concern, especially in restricted zones. The need to counter unauthorized drone operations is more prominent than ever. In this paper, we present an innovative end-to-end system that employs a defensive swarm of autonomous unmanned aerial vehicles (UAV) to effectively neutralize a swarm of invading drones. The main sectors affected by drone incidents between December 2018 and March 2020 were airports, private property, law enforcement, first responders and prisons [1].

1.1 Background on Drone Usage and Security Challenges

Several academic and technical efforts have been directed towards the creation of C-UAV systems. In a recent work [2], 537 C-UAV products have been identified. From such, only 138 encompasses detection and interdiction processes. From this number, only 3 of them have the capability of using a net as neutralization means combined with detection capabilities. Nevertheless, the detection is carried out by ground systems (e.g., radar) and not by a combination of ground and sky systems, such as we propose in our solution for an effective localization and tracking of intruders. In addition, there is not a product in this review that uses swarming as neutralization means as part of an end-to-end system from detection up to neutralization. Last, the inclusion of AI algorithms for real-world applications is very recent and seldom deployed.

There is a growing number of incidents by drone misuse [1]. Countering manually or with a single interdiction mean is not effective. Operating multiple drones to increase the chances of successful neutralization can potentially overwhelm operators. It is important to note that managing multiple drones to counter a single intruding drone is not a trivial task, not to mention the financial implications of training multiple operators and the operational costs themselves. Countering a swarm of drones is an even more complex operation, specifically due to drone coordination challenges.

1.2 Objective of the Research and the BlueSwarm System

This research aims at designing, developing, implementing and evaluating an innovative C-UAV system called BlueSwarm that can handle detection, tracking and neutralization of intruding swarms, leveraging a fleet of collaborative autonomous drones, for real world applications. Primarily, the system is devised to detect potential threats within a specified “buffer zone”, before they reach a “protected zone”. The system uniquely identifies and localizes the detected threats. Any tracked entity classified as intruder triggers a response from the defensive swarm for tracking purposes. If an intruder is detected and assigned for tracking by one or more agents of the swarm, an autonomous sensing control is initiated. The system then transitions to the neutralization phase when the defensive swarm’s positioning aligns with the neutralization criteria, and hence, proceeds to safe neutralization.

1.3 Description and Capabilities of the BlueSwarm System

Prior to real-world flight operations, the system is tested in simulation. The system (Figure 1), both during simulated and real-world demonstrations, integrates a radar, a PTZ camera, a defensive swarm of five drones, up to five intruding drones, one ground control station (GCS) per swarm, embedded cameras on each defending drone and a simulation station. Each drone and the GCS operate through their own AI agent. For real-world flight demonstrations, additional components are integrated to align with prevailing security and legal standards (e.g. manual drone controllers or a control STOP operations system). Field operators comprise technical personnel, security flight observers, pilots, and ground control station operators.

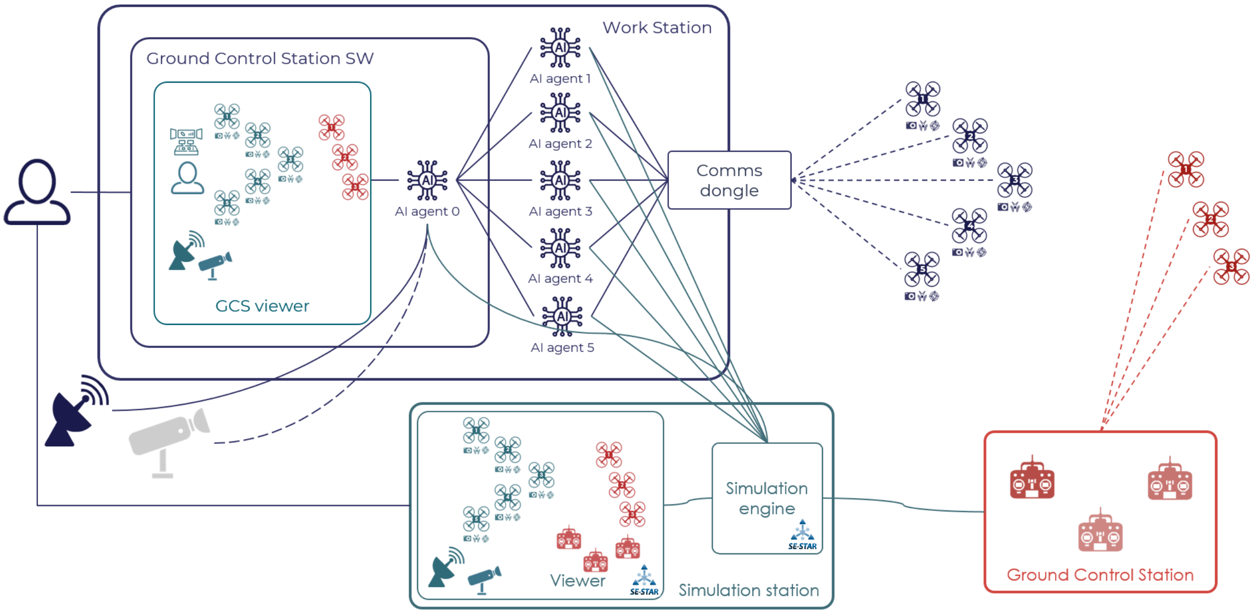

Figure 1: High-level architecture of the BlueSwarm system.

2.0 SYSTEM COMPONENTS AND ORGANIZATION IN SIMULATED AND REAL-WORLD ENVIRONMENTS

2.1 Overview of System Components

The BlueSwarm system is divided into a ground segment and an air segment, each composed of various hardware components. The efficiency of BlueSwarm is largely due to these carefully orchestrated elements. Stimulating our system for training and test purposes are a fleet of intruding drones and a number of simulators.

2.1.1 The Ground Segment

The ground segment is composed of a Ground Control Station (GCS), a ground radar and a ground PTZ.

The Ground Control Station (GCS) acts as the Communication Centre. Not only is it the human interface for the system but it also handles drone deployment, overall mission information, and coordination of system responses. The GCS features a GIS-based user interface that enables the human operator to interact with the system, monitor the ongoing mission, make informed decisions, and control desired system responses.

The long-range radar forms the first line of defense for our system. It is the pivotal component for early detection and classification of incoming threats over a vast radial distance, thereby providing ample response time. For the purpose of this project, we used a radar sensor that can detect drones at up to 1,000 m.

Alongside the ground radar, a PTZ camera provides complementary visual information to improve the quality of the long-range detection and classification. It serves to validate the classification based on radar tracks and helps improve the determination of the number of intruding drones thanks to its better resolution.

2.1.3 The Air Segment

The air segment is composed of a fleet of drones. Equipped each with an Electro-Optic sensor and a deployable net (simulated within the frame of this project), the defending drones serve as the primary countermeasure against intruding drones. Guided by AI agents with advanced decision-making and information processing algorithms, these drones work collaboratively to intercept and neutralize potential threats. They communicate with the defending Ground Control Station to relay captured information.

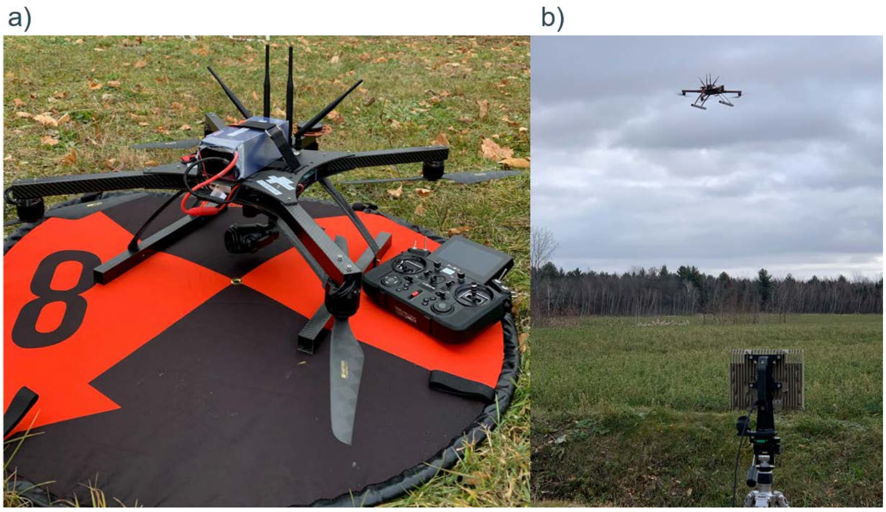

Figure 2: Drones manufactured by ARA Robotics®, landed (left) and during operations (right).

Each defending drone embeds a gimbal-mounted EO sensor. This sensor provides eyes-in-the-sky capabilities to the overall system. This component is crucial for target tracking and classification, in addition to the radar and ground PTZ. The embedded sensor is controlled in zoom and orientation by the AI agent of the platform it is embedded on.

2.1.4 Intruding Drones

The intruding drones' behaviors are designed to represent disruptive drone activities. They execute different patterns of careless, clueless or criminal operators. Much as the defending drones, each intruding drone is controlled by its own AI agent and communicates with the intruding Ground Control Station. For our live experimentations, defending and intruding drones are provided by ARA Robotics® and of the same model.

2.1.8 Simulators

We trained and tested our system using three different 3D simulators, gradually increasing in realism but also in complexity.

The first simulator is a multiple particle environment. It is the fastest and simplest. It draws the agents as simple particles where no physical constraints are considered other than speed limits, particle boundaries and momentum. This multiple particle environment, due to its speed, is used for training initial Machine Learning models.

The second simulator, Thales Group proprietary, is called SE-Star (Figure 3), and it approaches closer to the general conditions a swarm could face during a mission in the real world. This simulator uses a general physical dynamics model of the flying platforms. It is used for testing purposes and for fine-tuning the Machine Learning models previously learned using the first simulator.

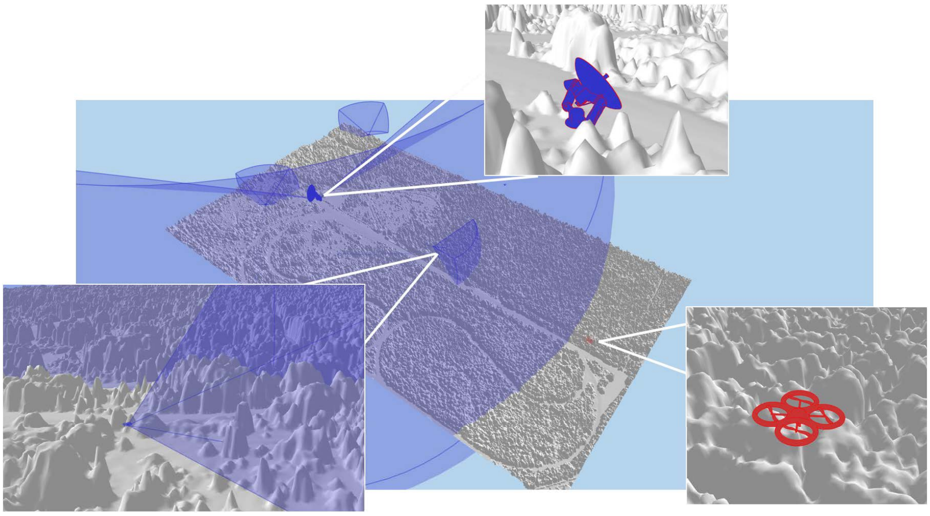

Figure 3: SE-Star simulates the ground sensors, the drones and their payloads.

The last simulator is embedded in SkyControl® (Figure 4), ARA Robotics®' GCS software. This simulator encompasses realistic dynamics of the actual quadcopters used for real-world demonstrations. It is used to reduce risks of potential conflicts during real flights. SkyControl® allows us to carry out high-quality tests and validation of our system prior to real world deployment.

Figure 4: SkyControl® user interface for simulation and real world flight trials.

2.2 Organization of Mission Phases

2.2.1 Detection, classification, localization and threat level assessment

The ground radar acts as an early warning sensor, detecting, classifying and localizing potential incoming threats at long range. Within the frame of our project, for real world demonstration, the radar sensor we used, was giving a detection range of up to 1,000 meters. The ground PTZ camera is the second sensor to be put in motion. Its purpose is to help confirm the nature and number of threats inbound thanks to computer vision. The GCS AI agent controls that sensor in pan, tilt and zoom, cued by the radar data.

The GCS AI agent also assesses the level of threat of the detected objects, assigning labels such as *enemy*, *friendly* or *neutral*, by information processing. The threat assessment process considers multiple aspects like size, speed, flight pattern, and radar cross-section of the intruding object. This process of detection, classification, localization and threat level assessment is not only the first step for deploying the defending swarm, but a continuous one throughout a mission.

2.2.2 Defending Swarm Deployment and Approach

Upon detection of an "enemy" (i.e., entity with an assigned *enemy* label), the system autonomously deploys the defending drones whose objectives are to approach, track and neutralize the threat(s). These drones move as a swarm towards the identified threat, with each drone being independently controlled by its own AI agent, constantly adapting to the mission phase it is engaged in. Each AI agent controls four interdependent decision-making functions. First, the Navigation function, allowing that AI agent to control the trajectory of its drone. Second, the Sensing function, giving control of the embedded EO sensor in pan, tilt and zoom to the AI agent. Third, the Neutralization function, letting the AI agent decide when to trigger its neutralization payload (i.e. its net). Last, the Targeting function, for the AI agent to assign itself a target drone. Those functions are realized thanks to decision-making algorithms that the AI agent orchestrates.

More specifically, each AI agent can switch between different decision-making algorithms for its Navigation function, depending on mission phases. To boost a collaborative behavior among the swarm, the Navigation policy used for approaching and tracking phases was learned by a Multi-Agent Deep Reinforcement Learning algorithm in order for those phases to be fast, coordinated and adaptable. However, the navigation during neutralization must be controlled, precise and explainable, thus a rule-based algorithm is preferred in our system.

For the Targeting function, the algorithm used ensures optimal allocation of targets among drones, reducing efficiency loss due to potential conflicts or repetition of tasks. For instance, the algorithm computes the best allocation by reducing the collaborative distance towards the available targets ensuring, and correcting, if necessary, so that no target is left within the buffer zone without being tracked by a drone of the defending swarm. This rule could only be broken if the number of intruders is higher than the number of drones of the defending swarm.

2.2.4 Tracking

Once the defending drones have reached the enemy drones, they enter a tracking phase. Depending on the number of enemy drones, one or more defending drones could be assigned to each enemy drone. The tracking is relying on a combination of radar and visual data as well as shared information among the swarm. A defending drone shall track its assigned target as long as it is not entering into a neutralization phase or as long as that target has not either exited the buffer zone or been neutralized.

2.2.5 Neutralization

The culmination of each mission is the neutralization of the intruding drones. Once a defending drone is tracking a target, it can volunteer for neutralization, based on criteria considering factors like proximity to the target, the position of other entities in the defensive swarm and net availability. That drone then deploys its net-based payload to scoop the intruding drone when it is approved to engage its target. While for the investigations of this paper, the engagement of a drone with a target is automatic, it is designed to be triggered by a human operator.

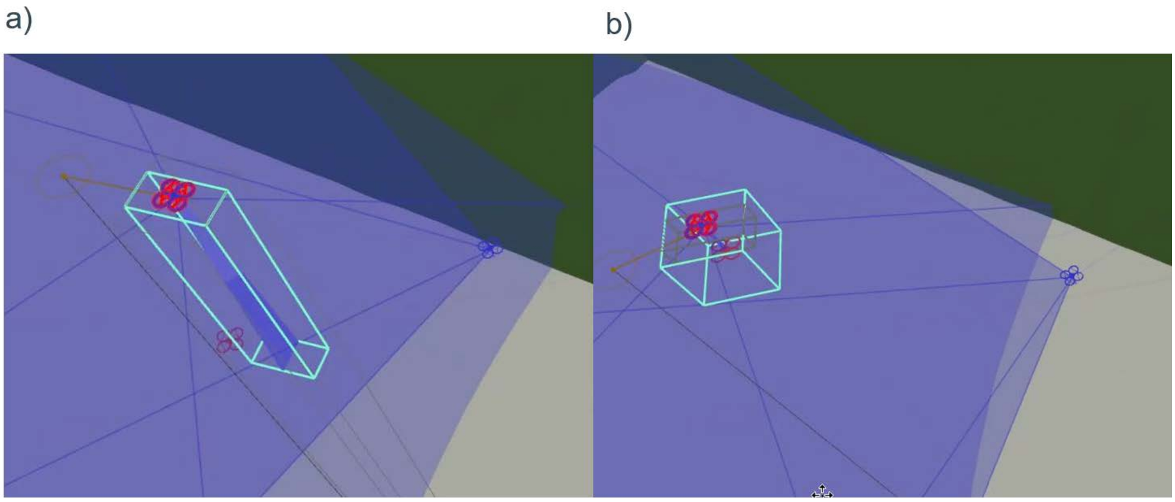

Figure 5: Net deployment and target capture in simulation. On the left, the drone engages in neutralization with the target and deploys its net after meeting the ready-to-neutralization conditions. On the right, target drone is captured. On both images, we observe how the drone to the right supports the visual tracking from a safe distance.

While the net system was proven successful in real flight operations, for our experiments we deploy the net only in simulated environments. A real net has not been used due to associated operational costs. During real world experimentations, telemetry data was fed into the simulator to virtually capture the drones.

3.0 USE CASES DEFINITION

Adaptability and versatility are core attributes of our system, allowing it to handle different scenarios and behaviors of drone intrusions efficiently. With inputs of subject matter experts, we defined several use cases representing typical intruding drone behaviors to test our system. Recent literature reports drone usage ranging from hobbyist [4], [5], delivery [6], photography [3] up to military and terrorist applications [7], [8].

We therefore derived four different drone operator's behavior models matching those applications, as illustrated on Figure 6:

1) Clueless operator: this use case represents typically hobbyists testing their drone, unaware of the nearby presence of restricted zones they could inadvertently fly over. The resulting drone behavior is rather erratic with lots of variation in velocity, heading and altitude.

2) Careless operator: in this use case, drone operators willingly ignore a known restricted airspace to leverage the shortest possible route e.g. for business purposes such as deliveries. The resulting drone behavior is rather constant in velocity, heading and altitude.

3) Criminal with no harm intended: this use case represents operators aiming to gain unauthorized access to restricted areas for the purpose of information acquisition but without the intent of causing direct harm. They might aim to capture photographs or videos as part of corporate espionage, criminal activities or simply as paparazzi or misguided fans. The resulting drone behavior is rather constant in heading, aiming for the protected zone, with a decreasing altitude to approach and a velocity increasing to reach the protected zone. The drone is not necessarily going into the protected zone, possibly skirting it and idling from time to time to take pictures.

4) Criminal with harm intended: in this most exigent use case, the operator intentionally breaches the protected zone with the objective of causing direct harm, such as a terrorist attack involving drones with explosive payloads. The resulting drone behavior is rather constant in heading, aiming for the protected zone, with a decreasing altitude to approach and a velocity accelerating in the last stretch to penetrate the protected zone effectively.

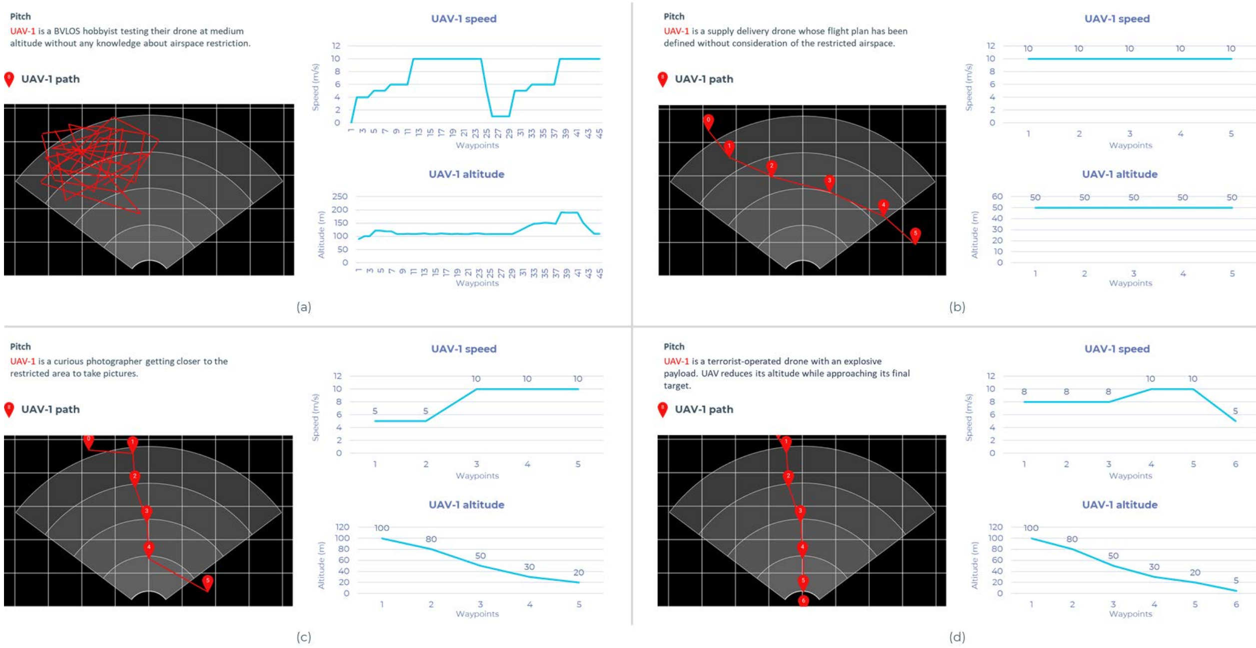

Figure 6: The 4 drone behaviors that we used as baseline to build our use cases with (a) the clueless operator, (b) the careless operator, (c) the criminal with no harm intended and (d) the criminal with harm intended.

We subsequently designed our use cases by determining the number of intruding drones, ranging between 1 and 5, and by choosing each intruding drone behavior model.

4.0 SYSTEM COORDINATION BETWEEN SWARM AGENTS

As illustrated on Figure 1 each drone's AI agent is not directly embedded on its drone. They are executed on the ground, in the workstation that is also hosting the GCS and the GCS' AI agent. This limitation is a choice of focus that was made, in line with the project's objectives that were to develop the AI agents and not focus on their embed-ability. However, from an architecture standpoint, notwithstanding the latency in communication, the system is operating as if the drones' AI agents were embedded on their own platform.

The collaboration of the AI agents and their swarming behavior is enabled through two means.

First, the AI agents are all communicating with each other, exchanging information pertaining to their perception of the situation they are facing. The perception that an AI agent has of the current situation is elaborated through the processing of the data captured by its platform sensors (the embedded gimbal-mounted EO for a drone's AI agent or the ground radar and the ground PTZ for the GCS's AI agent) as well as through the fusion of the resulting information and the information shared by the other AI agents. Through this process, we ensure that all AI agents have the same perception of the global situation with only a delta due to processing latency.

Second, our AI agents embed Multi-Agent Reinforcement Learning (MARL) algorithms to learn how to execute some specific decision-making functions (e.g., the navigation or the targeting) as a team. The policy that each AI agent learns embeds intrinsically the collaboration model enabling the swarming behavior at the system level since they were trained to execute the related function together.

Our system's interlinking communications between the swarm drones, the sensors and the GCS, allows for a seamless and coordinated response to any UAV threats, thereby upholding and protecting the restricted areas.

5.0 RESULTS IN SIMULATED AND REAL-FLIGHT OPERATIONS.

5.1 Simulations Results

In the simulated environment provided by SE-Star, we executed the four different use cases. Our C-UAV system displayed distinct stages from the monitoring up to the capture of five intruders.

1) **Monitoring and Detection:** Initially, after arming and take-off, the system was in an idle state, waiting for intrusions. Not until the appearance of unknown drones detected by the radar did it trigger actions.
2) **Intrusions:** Upon entering the buffer zone, unidentified drones were recognized as threats, causing our system to respond. The defense drones initiated interception paths to the intruders, and if multiple intruders were within the buffer zone, the defense drones would split for separate targets.
3) **System Engagement: I**f met with conditions confirming shortest distance between defending drone and target, alongside the availability of neutralization payloads (i.e., a net), the system transitions to a "ready to neutralize mode" waiting for further approval. This process prevents any redundant capture attempts. The approval is meant to be triggered by a human operator for future developments. In our trials, the approval was granted after an arbitrary delay representing the operator response time as the approval interface mechanism has not been implemented.
4) **Capture and release:** Once approved, the drone deploys its net to proceed with the capture, following which it transports the captured drone to a retrieval zone.

On all use cases, all the drones of the intrusion swarm were successfully intercepted, tracked and captured before they could reach the protected area.

5.2 Real Flight Operations Within Hybrid Environments

Real-world experimentations were conducted in a hybrid environment where all the BlueSwarm system's and red asset's hardware components were live except for the neutralization payloads, which were simulated. In order to be able to conduct complete missions, the system was mirroring the behavior of all real drones into SE-Star up until a neutralization phase was engaged. Once a neutralization phase was engaged, the behavior between the real drones engaged in that phase and their simulated counterparts diverged in order to allow for the neutralization to happen in the simulated world while maintaining safe conditions in the real world, to eliminate any collision risk during actual captures.

1) Monitoring and Detection: After arming and take-off, the system effectively classified environmental noise as non-threatening, keeping the drone idle.
2) Intrusion and Identification: As with the simulations, the system identified and classified drones as they entered the buffer zone.
3) System Engagement: In this phase, our system behaved similarly as during the simulated experimentations with the only difference that real-world perturbations (noise) were identified as neutral entities (e.g., birds) to allow our AI agent to take them into account for collision avoidance.
4) Capture Progression: In real-world operations, deploying the net was a virtual action conducted only in simulation. The success (or not) of the capture was therefore assessed in the simulated environment mirroring the actual situation. Upon capture, the behavior of the captured red drone was no longer mirrored in the real world. The simulated captured red drone was dragged by the simulated blue drone that captured it into the retrieval area. The real red drone however simply put itself out of the game by lowering its altitude below the buffer zone and remained ignored by the system until the end of the scenario. The real capturing blue drone moved towards the retrieval area, mimicking the fact of dragging the captured red drone and releasing it in that area. Its simulated counter-part was mirroring this behavior.

These adaptations in the system allowed us to successfully test various scenarios, encompassing the detection, localization, classification, tracking, neutralization and safe retrieval of captured targets in matches of two defending drones against two intruders.

6.0 CONTRIBUTION TO ADVANCEMENT OF SECURITY MEASURES

Our research design successfully exhibits the ability to tackle escalating drone threats, as demonstrated by our theoretical and practical executions. Notably, our system is designed to address an equal number of threats to the defensive swarm drones. Although, we must emphasize that this system is, for the moment, validated for small swarms only. This was substantiated during our simulated experiments and real-flight trials, where five drones managed to track an equivalent number of enemy drones in simulations, achieving a secure interception of all infiltrating units. In real-flight operations, our small defensive swarm of two drones coped with two enemy drones, confirming our system’s adaptability and scalability under different conditions and its promising application to real-world scenarios for future versions. To be noted also that our system is agnostic of the hardware equipment it is using. The drone make and model, the sensors type or the neutralization payload type can all be easily replaced or changed by different ones.

7.0 CONCLUSION

Our designed system showcased the integration of ground and air segments, entailing a range of sensors and countermeasure capabilities. By employing ground radar and PTZ camera, the system enabled long-range detection, classification, and localization of potential threats. Simultaneously the air segment contained a fleet of autonomous counter-UAVs, each equipped with an Electro-Optic sensor and a net deployment mechanism for neutralization purposes.

By synchronizing sensor data, facilitating communication among resources, and utilizing artificial intelligence, the counter-UAV system provided an end-to-end solution from detection to neutralization of intrusive drones. Priority was given to maintaining human oversight via a manned ground control station, thereby keeping the human operator in the loop for monitoring and a stop mechanism in case it was necessary for safety reasons. The stop mechanism consists of a “stop all” button that interrupts the commands during a mission from the AI agent to the drones. The stop button freezes the movement of all drones, defending or intruding, and gives back the control to the human pilots to manage the situation.

The system's architecture provides significant scope for scalability and adaptability responding to specific logistics and threat profiles of protected areas. Ground sensor types, quantity, and spatial distribution can be tailored according to user requirements, as can the number and payloads of the counter-UAVs.

One potential advancement could be the incorporation of an advanced visual and automatic threat level assessment capability. This would provide operators with a comprehensive understanding of imminent threats, reducing the risk for subjective errors whilst accelerating response time.

Strengthened by its resilience against evolving threats, adaptability to requirements, and the integration of leading-edge AI technologies, our system addresses a critical gap in unmanned aerial security. By refining and incorporating the system into existing infrastructure, we aim to safeguard restricted areas whilst mitigating the associated risks of unmanageable drone technology.

In line with NATO's vision toward reinforced security measures against drone threats, this research and system development, undertaken in collaboration with subject matter experts, marks a significant advance in counter-UAV technologies for real-flight operations. The envisaged future improvements and applications promise new impetus for technology transfer and further research within the NATO S&T community.

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Last, the team would like to thank the Royal Canadian Mounted Police (RCMP) for its help and review on the definition of the use cases and the red team behavior models.

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