Control and Coordination for Swarm of UAVs Under Multi-Predator Attack

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***Abstract*—This paper presents the implementation of a cooperative prey hunting strategy for a swarm of unmanned aerial vehicles (UAVs) inspired by the collective behavior of fish and predators. The swarm of UAVs are modelled using diffusion and adaptation algorithms, which enable self-organization and create mobile adaptive networks. Nodes in the mobile adaptive networks interact with each other locally to solve issues of distributed processing and inference. The predator motion is modelled using a state transition model. The study provides insights into the dynamic network structures that arise during interactions between a swarm of fish and predators. The dynamic model of the swarm of fish and predators are modeled using the unicycle model on a coplanar surface. A Lyapunov-based Backstepping controller is designed to ensure that the UAVs track their trajectories accurately. From the simulation results, it can be observed that both the swarm UAVs and the predator successfully tracks the designed navigation path while foraging, evading, and attacking, mimicking the air combat scenario.**

***Index Terms*—Cooperative Hunting, Multi agent system, Unmanned Aerial Vehicles, Bio-Inspired Algorithms, Backstepping Controller**

I. Introduction

Recent advances in the field of UAVs have increased their demand in various applications. These vehicles are increasingly becoming popular due to their versatility, cost-effectiveness, efficiency, and ease of operation. Their wide range of capabilities and applications make them an attractive option for various industries. UAVs can be utilized for a variety of purposes such as aerial photography, mapping, surveying, environmental monitoring, agriculture, package delivery, and even military operations [1]. With their ability to navigate through hard-to-reach areas and hazardous environments, UAVs have proven to be a valuable asset in operations that were previously deemed impossible or too dangerous. As the field continues to evolve, the potential applications for UAVs are expected to expand even further [2].

The use of multiple UAVs to coordinate and perform joint operation has significantly increased especially in the field of surveillance, monitoring, search and rescue operation or military combat operation [3]. Coordinating numerous UAVs is challenging but cooperative operation leading to success in terms of objective completed, minimized effort and cost and maximized efficiency has led to its widespread use. The coordination of multiple UAVs is often termed as swarming [4], [5]. Multiple UAVs are designed to work together as a collective unit, often resembling a swarm of bees or a flock of birds. Coordinating these systems requires sophisticated control and estimation techniques [6], [7].

In swarm UAVs, each individual unit operates autonomously, but also cooperates with other units to achieve a common goal. This requires complex communication and coordination strategies that ensure each unit is aware of its surroundings and the actions of other units. The use of swarm UAVs has numerous benefits, including increased flexibility, scalability, and robustness. These systems can adapt to changing environments and handle unexpected events, making them ideal for complex missions that involve multiple objectives [8].

To achieve successful coordination of swarm UAVs, a range of control and estimation techniques are employed. These techniques include algorithms for formation control [9], task allocation [10], and cooperative control [11]. Formation control algorithms are used to ensure that the swarm UAVs maintain a specific formation or pattern during their mission. Task allocation algorithms are used to assign specific tasks to individual units based on their capabilities and objectives. Cooperative control algorithms are used to ensure that the swarm UAVs work together effectively and efficiently.

The complex set of algorithms that enables the various components of the swarm to communicate with one another, coordinate their motions, and properly plan their trajectories in order to execute a goal is one of the essential techniques that enables swarming activity. The origin of swarm modelling can be attributed to flocking theory given by Craig Reynolds in 1987 [12]. Flocking behavior might be reframed as the basis for the cooperative hunting technique. Instead of just flocking another swarm, agents for the purpose of hunting use biologically inspired techniques such as chasing, encircling, and attacking.

A review on bio-inspired swarm robotics is discussed in [13]. In [14], an biological inspired algorithm is proposed for hunting in a multiple robots scenario. In [15], a cooperative hunting strategy for multi-robot based on the wolf swarm algorithm is presented. An improved artificial potential field method is utilized for cooperative hunting in a multi-robot scenarios in [16]. A biologically inspired control algorithm in [17], allows a multi-agent system to switch between navigation algorithms based on adaptive networks, diffusion, and adaptation techniques. The approach integrates path tracking, potential field strategies, to ensure stability during switching, formation maintenance, cohesive motion, mission completion, and predator evasion.

The objective of this paper is to expand upon the research presented in [4],from a single predator to a multi-predator attack scenario. Specifically, the study will investigate the cooperative hunting strategies employed by pods of dolphins when attacking baitballs, as described in reference [18]. The dolphins encircles the heard from all side, while individual members take turns plowing through the more condensed shoal to feed. Further a Lyapunov based backstepping controller is designed for trajectory tracking.

The paper is structured as follows: Section I serves as an introduction, Section II is system description where the UAV model is discussed as well the motion control mechanism of swarm and predator is discussed. In section III the state transition model is discussed, while in section IV the design of an backstepping controller is discussed. The simulation result is presented in section V. Finally the conclusion is made in section VI.

II. System Description

The swarm of UAVs and the predators are modelled using nonholonomic unicycle models [19]. Nonholonomic constraints imply velocity constraint cannot be integrated to provide positional constraint. Holonomic systems have integrable velocity limitations. In other words, holonomic constraints confine velocity but diminish configurational space and degree of freedom, whereas nonholonomic constraints do not. These UAVs are challenging to control since their velocity limits their position changes. Planar UAV kinematics include position, orientation, and two input velocities. The UAV navigation algorithm is designed using real-time node locations of the neighbouring UAVs, mobile threats (predator), and fixed desired goal (food source here) as in [4], [17].

The swarm UAVs navigate in two different modes, i.e., Foraging mode and evasion mode depending upon the location of the mobile threat. S.El Ferik et al. discussed the foraging, evasion and self organising behaviour of swarm of UAVs in detail in [4], [17]. As this work is a continuation of [4], the motion algorithms for swarm will not be discussed here. Instead, the focus will be on the mathematical modeling of the predators and the cooperative prey hunting strategy. The assumptions made for the swarm group in [4] remain the same for the predator group. The predator group updates its velocity and position based on the Eqn. (1).

$$\begin{aligned} v^p_{l,i+1} &= \lambda^p v^d_{l,i+1} + \gamma^p \delta^p_{l,i} \\ x^p_{l,i+1} &= x^p_{l,i} + \Delta t \cdot v^p_{l,i+1} \end{aligned} \tag{1}$$

Where $v^p_{l,i+1}$ is the velocity vector of the predator in each state during the cooperative hunting process as in Table I. And $x^p_{l,i}$ is the location of the predator l at time i. The overall speed of the predator $v^p_{l,i+1}$ is bounded by v^p_{max}. While λ^p, γ^p are non-negative weights and $\delta^p_{l,i}$ can be expressed as,

$$\begin{aligned} \delta^p_{l,i} = \frac{1}{|M_l| - 1} \sum_{l \in M_l \setminus \{k\}} \left(r_p - \left\| x^p_{l,i} - x^p_{j,i} \right\| \right) \cdot u \\ \cdot \left(x^p_{l,i} - x^p_{j,i} \right) \end{aligned} \tag{2}$$

And $x^g_{l,i}$ is the estimated location of the centre of gravity of swarm network by a predator l at time i. The predators cooperatively estimate the location of the Centre of gravity $x^g_{l,i}$ using the ATC algorithm [4]. while the location of the node of interest $w_{l,i}$ is estimated individually. This is because the predators are spread across the network in different direction and hence their node of interest are different. Thus, each predators estimate the position of node of interest $w_{l,i}$ using below equation.

$$\begin{aligned} w_{l,i} = w_{l,i-1} + v u^T_{l,i} [d_l(i) \\ - u_{l,i} \left(w_{l,i-1} - x^p_{l,i} \right)] \end{aligned} \tag{3}$$

Where, v is a step size. While $d_{l,i}$ and $u_{l,i}$ are the measured distance and the measured direction of the node by any predator l at time i [4]. The predators collectively hunt to increase their efficiency. The strategy of hunting can be divided into multiple modes or states based on the action of the predators. The hunting behavior of predator is modelled as state transition model [20] in the next section.

III. State Transition Model

The cooperative hunting behavior of the predator is modelled using state transition model with four possible states based on the action involved in the hunting process. The states are named as chase, encircle, trap and attack and are represented as S_0, S_1, S_2 and S_3 respectively. The state transition diagram for the predator is shown in Fig. 1.

The pursuit of predators begins with chase mode, S_0. Predators would approach the network of swarms and once the distance between the centre of gravity of the swarm group and predator group is equal to a predefined radii, the predator switches to encircle state, S_1. The predator then starts to encircle the network in a radius r_2 with origin at centre of gravity of network. When set to encircle, the predator group surrounds the swarm network over the circumference of the encircle orbit, while maintaining a constant distance between its peer node.

The predator maintains its orbit, while monitoring the swarm node position. The predator looks at the node farthest from the swarm network and evaluates if it's within the circle with radius $1.5r_2$. A node is considered an outlier if it is located far from the swarm network, i.e., $\| w_{l,i} - x^g_{l,i} \| > r_g$. As the predator

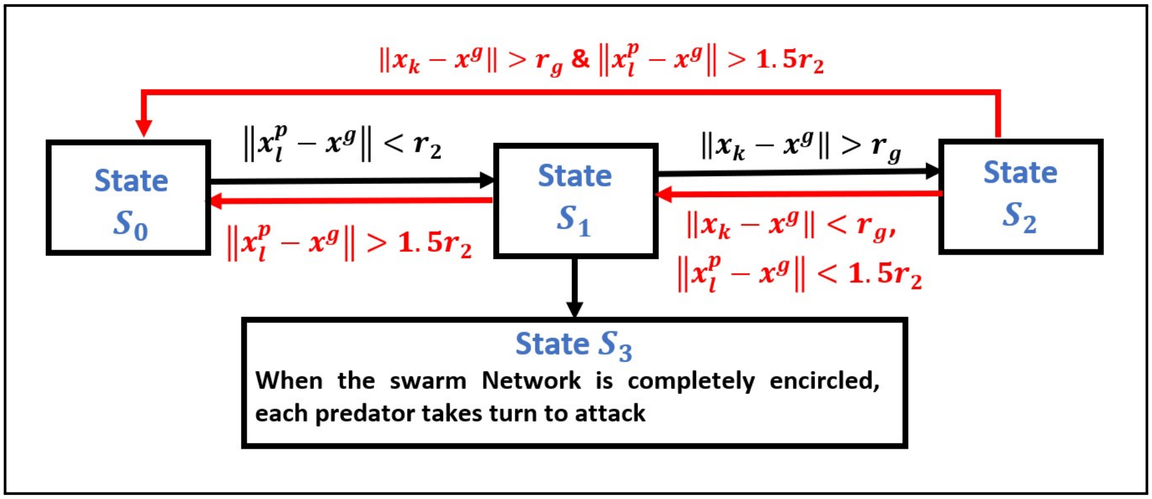

Fig. 1: State transition model for predator.

TABLE I. Equations Governing Predator velocity during each state

States	Governing Equations
State 0	$v^d_{l,i+1} = u\left(x^g_{l,i} - x^p_{l,i}\right)$ $x^g_{l,i}$ and $x^p_{l,i}$ is same as stated above.
State 1	$v^d_{l,i+1} = c_2 \cdot u\left[\left(x^p_{l,i} - x^g_{l,i}\right)^{\perp}\right]$ Where $c_2 = \pm 1$, (+1 for counterclockwise and -1 for clockwise). If right semicircle is empty, $c_2 = +1$ and if left semi-circle is empty $c_2 = -1$, else c_2 can be randomly $+1$ or -1.
State 2	$v^d_{l,i+1} = \begin{cases} u\left(w_{l,i} - x^p_{l,i}\right) & \text{if } \left\|w_{l,i} - x^p_{l,i}\right\| > 1.5r_3 \\ -u\left(w_{l,i} - x^p_{l,i}\right) & \text{if } \left\|w_{l,i} - x^p_{l,i}\right\| < r_3 \\ c_3 \cdot u\left[\left(w_{l,i} - x^p_{l,i}\right)^{\perp}\right] & \text{otherwise} \end{cases}$ Where $c_3 = \pm 1$ depending upon the inner product of $(w_{l,i} - x^g_{l,i})^T (x^p_{l,i} - w_{l,i})^{\perp}$. If the inner product is greater than zero c_3 is 1, else -1.
State 3	$v^d_{l,i+1} = u\left[w_{l,i} + \Delta t.v_{l,i} - x^p_{k,i}\right]$ where $v_{l,i}$ is the velocity estimate of the swarm node by any predator l at time instant $i.v_{l,i}$ is estimated [4].

spots an outlier, it immediately enters Trap state $S2$ and drives back the escaping swarm node into the network center. If there are no outliers detected, the predators takes turn to attack the swarm network. As one predator attacks, the others maneuver to surround the swarm of UAVs to prevent any potential escape. The velocity vector of the predator in each state is updated as in Table I.

IV. Backstepping Controller Design

In this section we shall design a trajectory tracking controller and ensure that the swarm and predator UAVs follow the designed navigation algorithm. The designed controller is based on lypaunov theory [21]. We divide the system dynamics into two subsystem. The first subsystem consist of angle error dynamics, and the second subsytem includes the position error dynamics. Initially, a lyapunov-based control strategy is utilized to reduce the error in the orientation angle to zero. Then, a control approach following the backstepping methodology is formulated to bring the error in the robot's position to zero. Initially, the developed controller is incorporated with a singular UAV, and an analysis of tracking using a single UAV is carried out. Subsequently, the identical control methodology is applied to a fleet of UAVs.

Single UAV Tracking

The kinematic model of a planar UAV (unicycle model) is similar to [4]. The error dynamics can be obtained and rearranged as in Eqn (4).

$$\begin{aligned}\dot{\theta}_e &= \omega_d - u_2 \\ \dot{y}_e &= v_d \sin(\theta_e) - u_2 x_e \\ \dot{x}_e &= v_d \cos(\theta_e) + u_2 y_e - u_1\end{aligned} \tag{4}$$

Where u_1 and u_2 are the linear and angular velocity and control variables. And it is assumed the referenced linear and angular velocities are bounded such that $v_d \neq 0$ and $\omega_d \neq 0$. The error state goes to zero when the reference and actual states are equal. The control input that ensure that the tracking error goes to zero is given by Eqn (5) and (6) respectively.

$$u_2 = k_1\theta_e + \omega_d \tag{5}$$

$$u_1 = v_d \cos(\theta_e) - v_d u_2 \sin(\theta_e) + u_2^2 x_e + k_2\chi \tag{6}$$

Subsystem I: The angle error subsystem is given by $\dot{\theta}_e = \omega_d - u_2$, and that the control input that makes the system asymptotically stable is given by Eqn (5).

Proof: we define a lyapunov function candidate as,

$$V_o(t) = \tfrac{1}{2}\theta_e^2$$

Differentiating $V_o(t)$ with respect to θ_e to prove the convergence of the trajectory, therefore,

$$\dot{V}_0 = \theta_e\dot{\theta}_e = \theta_e(\omega_d - u_2)$$

Substituting the control law from Eqn(5), we get

$$\dot{V}_0 = -k_1\theta_e^2$$

Since k_1 is positive scalar therefore, $\dot{V}_0$ is negative definite, then as $t \to \infty$, $\theta_e \to 0$.

Subsystem II: The Second subsystem defines the robots position error dynamics given by Eqn(7)

$$\begin{aligned}\dot{y}_e &= v_d \sin(\theta_e) - u_2 x_e \\ \dot{x}_e &= v_d \cos(\theta_e) + u_2 y_e - u_1\end{aligned} \tag{7}$$

We now define an auxiliary control variable $z = v_d \cos(\theta_e) + u_2 y_e - u_1$ such that Eqn(7) can be rewritten as in Eqn(8) which is in the desired form of backstepping control design.

$$\begin{aligned}\dot{y}_e &= v_d \sin(\theta_e) - u_2 x_e \\ \dot{x}_e &= z\end{aligned} \tag{8}$$

From Backstepping control theory x_e is treated as virtual control law such that $x_e = \psi(y_e)$. we first design a control law z to asymptotically stabilise the complete system. We assume that the error dynamics of the robots position error in Eqn (8) goes to zero under the control law z defined as,

$$z = -u_2^2 x_e + u_2 v_d \sin(\theta_e) + u_2 y_e - k_2\chi \tag{9}$$

Where k_2 is a positive scalar, and $\chi = x_e - \psi(y_e)$ and,

$$\psi(y_e) = u_2^{-1} v_d \sin(\theta_e) + u_2 y_e \tag{10}$$

Proof: The first step is to design a virtual control law to stabilise the ($\dot{y}_e$) dynamics. Let the Lyapunov function candidate be given as $V_1(y_e) = \frac{1}{2}y_e^2$. The time derivative is obtained as,

$$\dot{V}_1(y_e) = y_e\dot{y}_e = y_e(v_d \sin(\theta_e) - u_2 x_e)$$

$$\dot{V}_1(y_e) = y_e v_d \sin(\theta_e) - y_e u_2 x_e$$

if we take $x_e = \psi(y_e) = \frac{1}{u_2} v_d \sin(\theta_e) + u_2 y_e$ then $\dot{V}_1(y_e) = -y_e^2 u_2^2 \leq 0$. As $\dot{V}_1(y_e)$ is negative, hence $y_e(t)$ is stable and $y_e \to 0$ as $t \to \infty$.

Now the second step is to design a control law $z(t)$ such that the position error of the complete system goes to zero. We can rewrite the system in Eqn(8) as below,

$$\begin{aligned}\dot{y}_e &= v_d \sin(\theta_e) - u_2(\chi + \psi(y_e)) \\ \dot{\chi} &= \xi\end{aligned} \tag{11}$$

where

$$\chi = z - \dot{\psi}(y_e) \tag{12}$$

and

$$\dot{\psi}(y_e) = u_2\dot{y}_e \tag{13}$$

Now we consider another Lyapunov function candidate as,

$$V_2(t) = \tfrac{1}{2}y_e^2 + \tfrac{1}{2}\chi^2$$

Differentiating $V_2(t)$ along the trajectory of Eqn (11) we get,

$$\dot{V}_2 = y_e\dot{y}_e + \chi_e\dot{\chi}_e = y_2(v_d \sin(\theta_e) - u_2(\chi + \psi(y_e)) + \chi\xi$$

Substituting $\psi(y_e)$ from Eqn(10) and ξ from Eqn (12) we get,

$$\dot{V}_2 = -u_2^2 y_e^2 - u_2 y_e \chi + \chi\left(z - \dot{\psi}(y_e)\right)$$

Finally, substituting Eqn(13) and using the control law in Eqn(9) gives

$$\dot{V}_2 = -u_2^2 y_e^2 - k_2\chi^2$$

Since $\dot{V}_2 < 0$, it can be concluded that the system is asymptotically stable. And as $t \to \infty$ both position error x_e and y_e tend to zero. Finally we get the linear velocity control input as, given that $u_2 = k_1\theta_e + \omega_d$

$$\begin{aligned}u_1 = &v_d \cos(\theta_e) - v_d u_2 \sin(\theta_e) \\ &+ u_2^2 x_e + k_2\chi\end{aligned}$$

V. Simulation Results

Firstly the simulation results for a single UAV tracking is carried out to illustrate the effectiveness of the designed controller. The gain parameters k_1 and k_2 are 0.8 and 0.5 respectively. The desired linear and angular velocity are chosen as $v_d = 0.5$ and $w_d = 0.5$. The initial condition for error model in Eqn.(4) is $[x_e(0), y_e(0), \theta_e(0)]^T = [1.0, 0.8, 1.0]^T$.The simulation result for state error convergence and trajectory tracking is shown in Fig. 2.

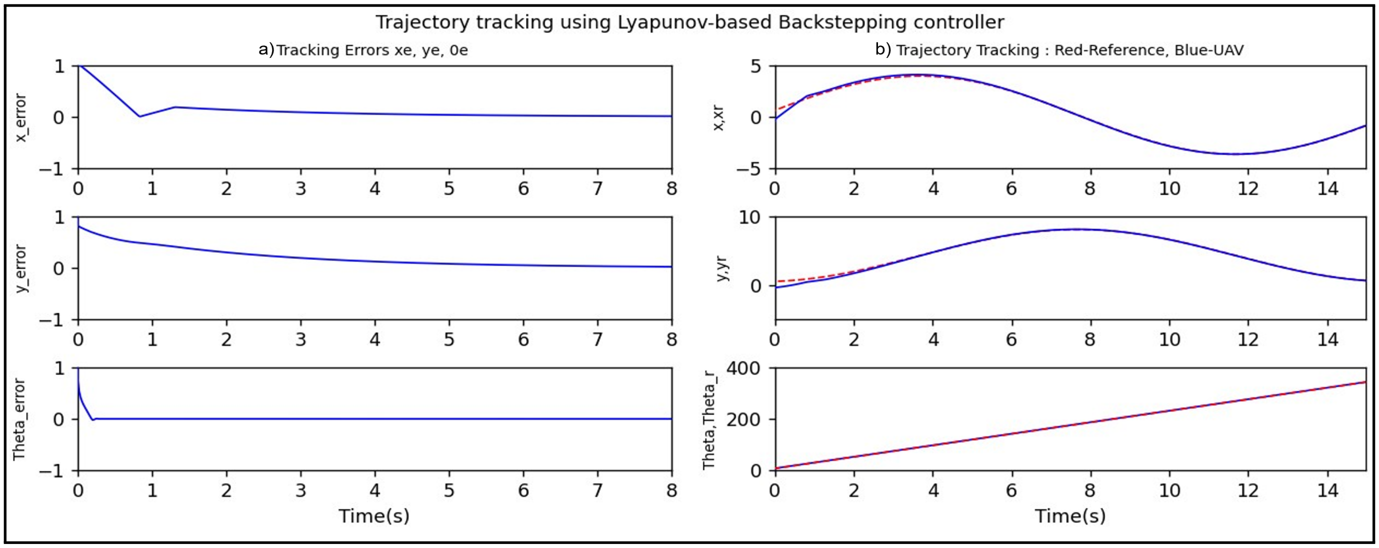

Fig. 2: Single UAV (a) state error convergence (b) reference tracking.

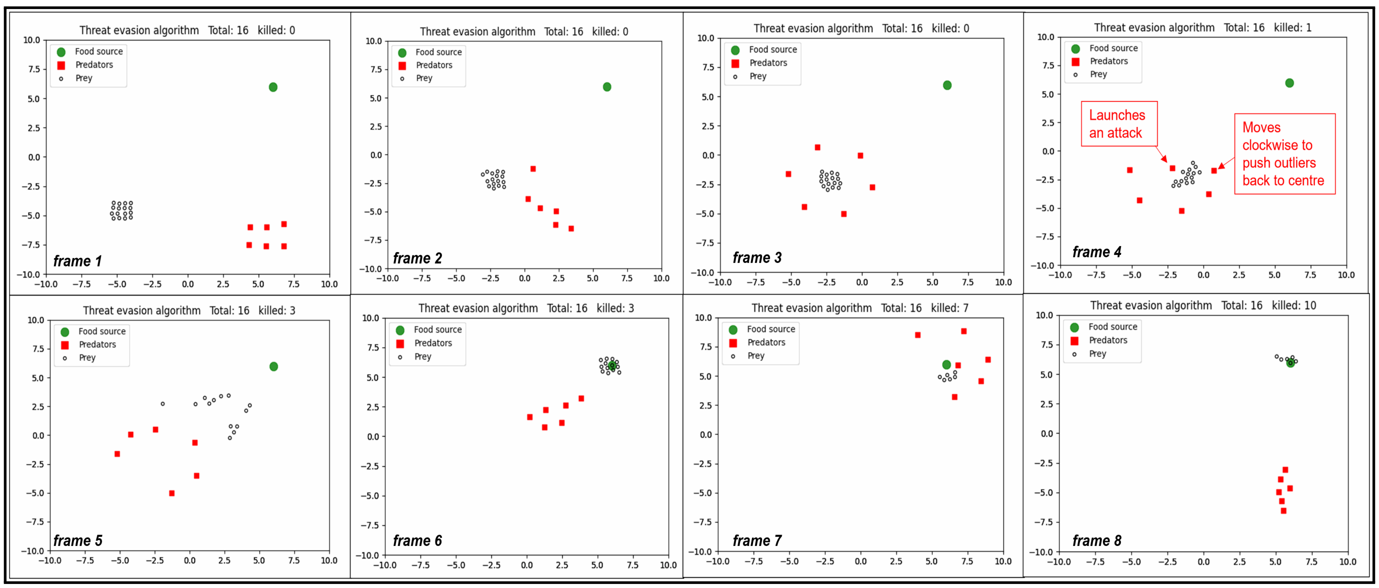

Fig. 3: Multi-predator attack, frame 1-8.

The simulation results for cooperative hunting strategy involving multiple predators is presented in Fig. 3 . The scenario involves a herd of six predators attacking 16 swarms of UAVs foraging towards a food source. The predators are seen chasing and successfully encircling the fleet of UAVs before launching an attack. Meanwhile, the swarm of UAVs attempts to escape and evade the attack. These results showcase an air combat warfare scenario with multiple attackers.

The initial position of the predators has been set in the fourth quadrant as shown in Fig. 3, *frame 1*. The Predator UAVs starts to chase the Fleet of UAVs foraging on a mission to reach a stationary target at (6,6) as shown in *frame 2*. The predator is in State 0 i.e., Chase. The predator group can be seen going across the fleet of UAVs to block them from foraging and encircles them completely as shown in *frame 3* the predator is now in state 1, i.e. Encircle. In the next *frame 4* one of the predator launches an attack on the Fleet of UAVs, while other predators move either clockwise and anticlockwise to push outliers back to the network centre. The predator group is now in State 2 i.e., Attack.

Once the attack is initiated the Fleet of UAVs tries to evade and escape the attack as shown in Fig 3, *frame 5*. The predator group is again in state 0, i.e. Chase. The predator chases the swarm UAVs as shown in *frame 6* and again encircles it and launches next set of attack as shown in *frame 7*. The swarm of UAVs again tries to escape the attack. while in the process some UAVs which come directly in contact with the predator UAVs are eliminated/killed and some of the UAVs move out of the simulation environment to escape the attack and are invisible to the predator and thus are marked safe. The predator continues to attack the UAVs until all the UAVs are either killed or escape. once all the swarm UAVs are killed or escape the predator return back to initial position, while the UAVs which managed to escape return back to their food location as shown in *frame 8*.

VI. Conclusion

Our work demonstrates the successful implementation of bio-inspired algorithms for a multi-agent system. The navigation algorithms were designed using diffusion and adaptation technique, while laypunov-backstepping controller was developed to ensure precise trajectory tracking of the swarm of UAVs. The simulation results vividly illustrate the effectiveness of our approach, as the swarm of UAVs and predators were able to navigate smoothly without any collisions. Our implementation of a cooperative hunting strategy for the predators is particularly noteworthy, as it could be used in the future to replicate air combat scenarios in warfare with a set of drones. To further enhance the complexity of the scenario, unstructured obstacles and moving targets could be introduced. Additionally, Artificial Intelligence and Machine Learning can be introduced to add intelligence to the foraging and evasion of UAVs.

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