Effect of Multiple Predators on Particle-Based Predator-Prey Interactions

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***Abstract*—Swarm robotics is an emerging field that aims to develop autonomous systems capable of performing complex tasks in uncertain environments. Understanding the interactions between agents in a swarm and their environment is critical for designing effective swarm robotics systems. In this paper, we investigate the effect of predator-prey interactions on swarm robotics behavior through simulation, which allows for a controlled study of different parameters that would be difficult to replicate in real-world scenarios. Our results demonstrate the importance of predator-prey interaction gains in designing efficient and robust swarm robotics systems, and provide insights into the underlying mechanisms that govern swarm behavior. We highlight the potential of simulation-based approaches for studying complex systems and optimizing swarm robotics algorithms.**

I. Introduction

Swarm robotics has emerged as a promising field for designing autonomous systems capable of performing complex tasks in uncertain and dynamic environments. A key feature of swarm robotics is the ability of multiple robots to work together in a coordinated manner, resulting in emergent behavior that can be adapted to a wide range of tasks. Understanding the interactions between individuals in a swarm and their environment is critical for designing efficient and robust swarm robotics systems. One of the most intriguing aspects of swarm behavior is the predator-prey relationship, which has been widely studied in nature, such as in schools of fish, animal stampedes, or herding sheep, as can be seen in Figure 1. In this paper, we investigate the impact of various predator-prey interactions with multiple predators on swarm robotics behavior, building upon the work of Chen and Kolokolnikov who explored the impact of single predator-prey interaction strategies [1]. By exploring the effects of multiple predators on swarm behavior, we aim to shed light on the underlying mechanisms that govern swarm behavior and provide insights for designing effective swarm robotics systems.

Fig. 1. Sheepdogs herding in groups

II. Related Work

Predator-prey interactions are fundamental to the dynamics of many ecological systems, ranging from terrestrial ecosystems to marine environments. Understanding the behavior of predator-prey interactions in groups or swarms, where prey animals exhibit collective behaviors, has garnered increasing attention in recent years. In particular, the work by Chen and Kolokolnikov [2] has provided insights into the dynamics of such interactions using a simple mathematical model.

Chen and Kolokolnikov initially focused on studying the effects of a single predator on a swarm of prey in their minimal model. They considered a scenario where a single predator interacts with a swarm of prey particles that move collectively according to alignment, cohesion, and repulsion rules. The prey particles are modeled as point particles that exhibit flocking behavior, aligning their velocities with their neighbors, maintaining cohesion with nearby particles, and avoiding collisions with each other.

However, in real-world scenarios, multiple predators may be present, and the interactions between multiple predators can play a crucial role in shaping the dynamics of the predator-prey system. For example, in a recent study by Ordaz-Rivas et al. [3], a flock of robots with self-cooperation was used to investigate the predator-prey dynamics. In their work, the robots were programmed to exhibit collective behaviors, similar to the flocking behavior of prey particles in Chen and Kolokolnikov's model. The robots cooperatively herded virtual prey particles towards a designated goal area while avoiding obstacles.

The study by Ordaz-Rivas et al. demonstrated that the coordination among multiple predators, in this case, robots, can significantly impact the efficiency and effectiveness of the predator's behavior. The robots were able to effectively herd the prey particles by coordinating their movements, and the presence of multiple predators improved the overall performance of the predator-prey system. This highlights the importance of considering interactions among multiple predators in predator-prey systems, as it can lead to emergent behaviors and impact the dynamics of the system.

A previously studied phenomenon is that of predator confusion, which is when a predator is 'confused' as to which individual prey to pursue, as mentioned in [1]. There are also examples in nature and several other papers that study this behavior [4]. By simulating the prey-predator interactions, we hope to analyze what factors contribute to a 'confused' single predator. For example, in nature a single lion would not be able to catch its prey as it is not fast enough to catch any member of the flock, however with the introduction of many equal speed lions they are suddenly able to catch their prey. Currently we can measure whether a predator is confused by observing the total force acting upon the particle. In examples where the predator is confused, the total force is very close to 0, while when the predator oscillates in the center of the flock, the magnitude of the force does not approach 0 thus continuing the motion. Thus measurement can be used to determine whether the predators have reached a steady state of confusion, and can be expanded to measure the collective confusion of multiple predators

Another behavior that may be observed in nature is that of collective hunting. In [5], the authors investigated cooperative hunting behaviors by killer whales. They observed that the whales had two different travel modes depending on their environment, specifically dependent on the presence of ice. In open water, they travelled in a fairly tight group, while in areas of packed ice, they travel as individuals while 'spying' for seals (prey) on the ice. In the simplified model that we are implementing, we can study the effect of 'tighter' groups of predators (stronger attractive force between predators) and the effect on hunting.

Drawing inspiration from the study by Ordaz-Rivas et al., our investigation will extend the work of Chen and Kolokolnikov by exploring how the coordination of multiple predators can affect the behavior of prey particles in a swarm robotics system. We will examine how introducing multiple predators into a prey swarm, and introducing repulsion and attraction laws between predators affect coordination strategies and the collective behavior of the prey swarm. By integrating insights from the work of Chen and Kolokolnikov with the findings of Ordaz-Rivas et al., our study aims to provide a comprehensive understanding of the dynamics of predator-prey interactions in the presence of multiple predators, and contribute to the advancement of swarm robotics systems for predator-prey tasks.

III. Methodology

A. Single Predator Model

In our investigation we will be adapting the particle-based model used by Chen and Kolokolnikov to account for multiple predators. Chen and Kolokolnikov's initial model consisted of the following equations to determine the velocity of each predator and prey respectively:

$$\frac{dx_i}{dt} = F_{prey-prey} + F_{prey-predator} \tag{1}$$

$$\frac{dz}{dt} = F_{predator-prey} \tag{2}$$

where x_i represents the 2D position of the i^{th} prey, and z represents the 2D position of the predator. With these models, the prey's velocity is the sum of two components, the average force between this prey and every other prey in the swarm $F_{prey-prey}$, and the force between this prey and the predator $F_{prey-predator}$. Chen and Kolokolnikov modeled the forced between x_i and any other prey x_n using a Newtonian-type Short-range repulsion in the form $\frac{x_i - x_n}{|x_i - x_n|^2}$ and linear long range attraction; $a(x_i - x_n)$ with the scalar a allowing for tuning of the repulsion-attraction ratio. By averaging these forced among all the prey in the swarm the resulting $F_{prey-prey}$ can be calculated as $\frac{1}{N}\sum_{n=1,n\neq i}^{N}(\frac{x_i - x_n}{|x_i - x_n|^2} - a(x_i - x_n))$. Additionally, $F_{prey-predator}$ was similarly modeled using Newtonian-type short range repulsion in the form $b\frac{x_i - z}{|x_i - z|^2}$ where b allows for the scaling of this force. To calculate the velocity of the predator z Chen and Kolokolnikov decided to use a short-range attraction in the form $\frac{x_n - z}{|x_n - z|^p}$ where p turns each individual interaction into a power law, which decays at large distances. This results in the following models for prey and predators respectively

$$\frac{dx_i}{dt} = \frac{1}{N}\sum_{n=1,n\neq i}^{N}(\frac{x_i - x_n}{|x_i - x_n|^2} - a(x_i - x_n)) + b\frac{x_i - z}{|x_i - z|^2} \tag{3}$$

$$\frac{dz}{dt} = \frac{c}{N}\sum_{n=1}^{N}\frac{x_n - z}{|x_n - z|^p} \tag{4}$$

B. Multiple Predator Models

To expand Chen and Kolokolnikov's model to include multiple predators, we had adapt $F_{prey-predator}$ to calculate the resulting force as an average of all predators. We maintained the Newtonian-type short range repulsion in the form $\frac{1}{M}\sum_{m=1}^{M} b\frac{x_i - z_m}{|x_i - z_m|^2}$. This resulted in the following formula for calculating each prey and predator velocities:

$$\frac{dx_i}{dt} = \frac{1}{N}\sum_{n=1,n\neq i}^{N}(\frac{x_i - x_n}{|x_i - x_n|^2} - a(x_i - x_n)) + \frac{b}{M}\sum_{m=1}^{M}\frac{x_i - z_m}{|x_i - z_m|^2} \tag{5}$$

$$\frac{dz_j}{dt} = \frac{c}{N}\sum_{n=1}^{N}\frac{x_n - z_j}{|x_n - z_j|^p} \tag{6}$$

As many predators do not act alone while hunting flocking prey we decided to further introduce interactions between predators. As a result we updated equation (2) to include a $F_{predator-predator}$ term:

$$\frac{dz}{dt} = F_{predator-prey} + F_{predator_predator} \tag{7}$$

When developing the $F_{predator-predator}$ term, we introduced two components. First we integrated another Newtonian-type short-range repulsion between z_j and z_m in the form $d\frac{z_j - z_m}{|z_j - z_m|^2}$. Second we introduced a linear long range attraction in the form $e(z_j - z_m)$. We felt these components were necessary so predators do not overlap with one another and reduce their effective coverage of the swarm, while still maintaining an attraction to one another allowing them to achieve coordinated motions. We also introduced d and e values to scale these repulsive and attractive forces respectively.

As a result our model for multiple predators with interactions is as follows:

$$\frac{dx_i}{dt} = \frac{1}{N} \sum_{n=1, n\neq i}^{N} \left(\frac{x_i - x_n}{|x_i - x_n|^2} - a(x_i - x_n) \right) + \frac{b}{M} \sum_{m=1}^{M} \frac{x_i - z_m}{|x_i - z_m|^2} \quad (8)$$

$$\frac{dz_j}{dt} = \frac{c}{N} \sum_{n=1}^{N} \frac{x_n - z_j}{|x_n - z_j|^p} + \frac{1}{M} \sum_{m=1}^{M} \left(d\frac{z_j - z_m}{|z_j - z_m|^2} + e(z_j - z_m) \right) \quad (9)$$

C. Model Integration and Behavior

To collect data on the behavior of swarms with multiple predators we implemented provided equations in Python using Numpy and Matplotlib. We utilized 2D vectors to represent each agent's position and velocity (both predators and prey). While calculating the velocity of each agent at any timestep we pass in the positions of the predators and prey alongside the gains a, b, c, d, e, p to calculate $F_{prey-prey}$, $F_{prey-predator}$, $F_{predator-prey}$ and $F_{predator-predator}$ which can be summed into the resulting velocities using formulas (1), (7). With these position and velocity vectors we can use the Matplotlib quiver function to visualize the current state of each predator and prey as shown in Figure 2

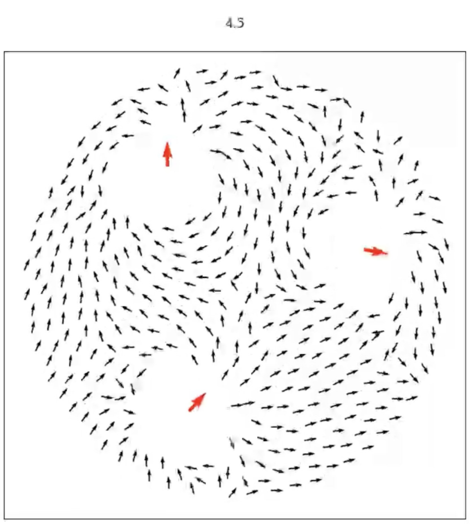

Fig. 2. Sample Visualization

While verifying the implementation of these formulas we observed several interesting behaviors as shown in Figure 3. Notably as in Chen and Kolokolnikov's work we found that depending on the model's parameters, the behavior would fall into 3 categories including, prey escaping, predator confusion, and chaotic behaviors. As stated in the title, when the predators are not able to move fast enough, the prey escape their short range attraction and successfully evade capture. Alternatively if the predators can move too fast then their motion becomes chaotic as while the $F_{predator-prey}$ power law causes long-range decay of the force, it conversely causes a short-range explosion of forces. In between these two states, the predators exhibit certain amounts of confusion, however we saw 3 distinct forms of confusion. First the predators could reach a stable state where all forces acting upon them cancel out and they cease to move or chase any prey. Second the predators could fall into unstable oscillations where they move in smaller circles around various areas of the flock. Lastly with certain d and e parameters we also noticed that the velocities of each predator ended up tangent to the edge of the flock and they would end up circling the center of the flock in a coordinated manner.

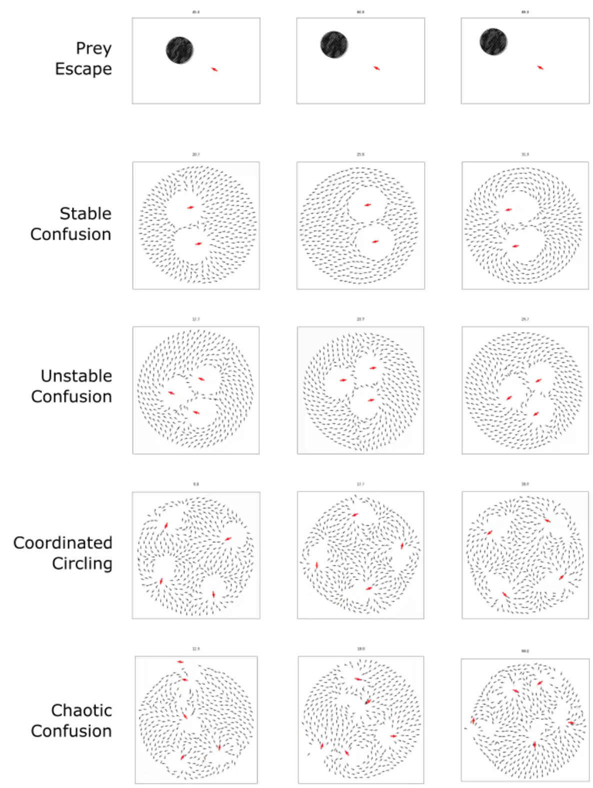

Fig. 3. Observed behaviors characterization

D. Data Collection Methods

In our experiments we wanted to find two metrics of the predators. Firstly we wanted to measure the predators effectiveness by implementing a kill radius r. This served as a zone where if any prey fell within the specified radius of any predator, then the predator swarm was labeled as successfully catching the prey. Secondly, we manually classified each model's behavior after each simulation.

To gather this data we randomly initialized N prey and M predators in an evenly distributed circle about the origin of the field with the same random seed. This ensured the starting position of predators and prey remained consistent between simulations and any behaviors were reproducible.

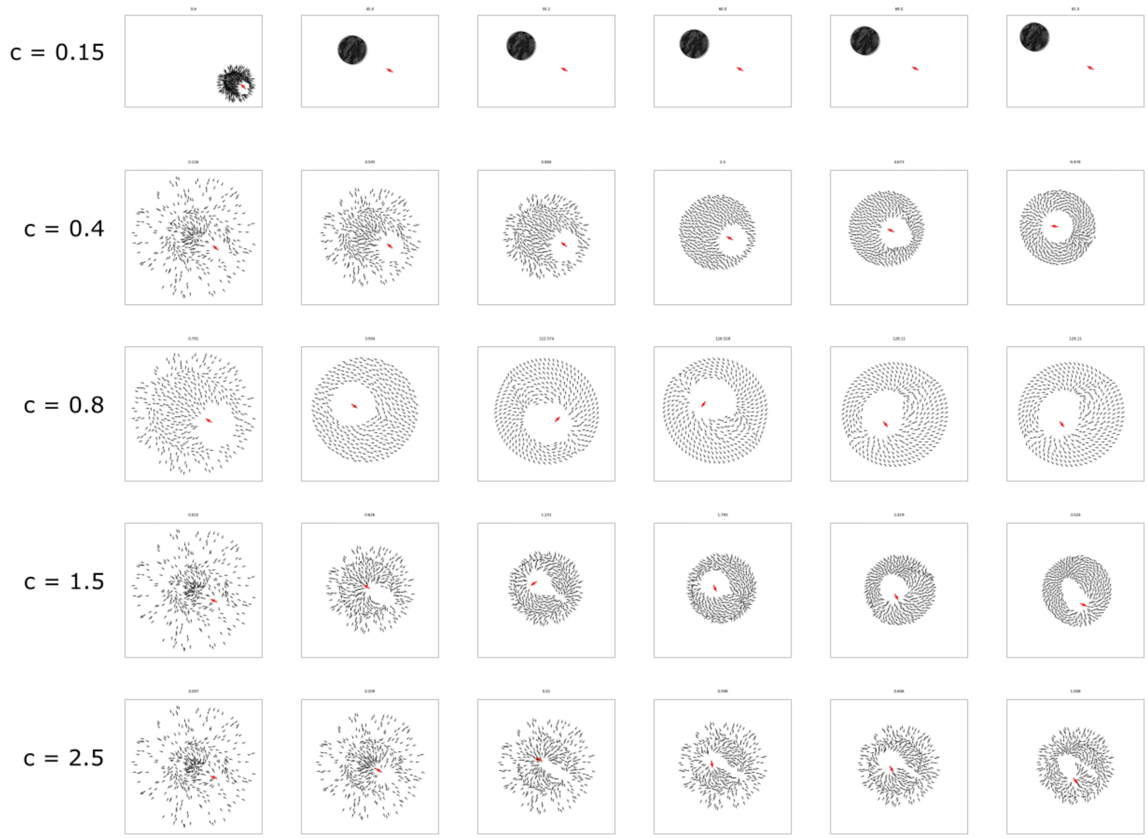

Fig. 4. Our replication of previous work by Chen and Kolokolnikov.

Next we ran each model for a specified number of time steps T, recorded whether any predators caught a prey, and exported the visualization of the model to a .mp4 file. This allowed us to observe behaviors after running the model once and return to any models for further analysis.

While running our experiments we found that running models with larger numbers of prey took exceedingly long to run and export. As a result we used Numba to pre-compile the models into optimized machine code to expedite the collection of data. Additionally we developed a pipeline that allowed simulation frames to be directly sent in argb form to hardware encoders on a computer's CPU/GPU using ffmpeg, reducing the export time of videos to 10% of Matplotlib's default implementation. This allowed us to investigate more variables and effects in the given time.

After exporting these videos, we watched every simulation and manually labeled the observed behaviors and recorded the results in CSV files for later parsing and visualization. Once the data was amassed we further used Matplotlib to generate heatmaps of catching success and behaviors as discussed in later sections.

IV. Experiments

We simulated many experiments grouping into three main categories. First, we replicated the work of Chen and Kolokolnikov in order to evaluate the performance of our model and to make sure it worked correctly. Second, we introduced multiple predators into the environment without any interaction between one another. This would simulate different predators that did not care about each other within an environment. Lastly, we introduced multiple predators with interaction between them, same as the interaction between prey. This allowed us to simulate prey that wanted to work together and maintain some distance between one another.

A. Replication of Previous Work

We first wanted to replicate the work of Chen and Kolokolnikov, as it would be a good starting point to make sure that our simulation was going to be an accurate comparison. For this experiment, we used the model (3) and (4). We set the parameters to $N = 400$, $a = 1$, $b = 0.2$, $p = 3$, and $c \in [0.15, 0.4, 0.8, 1.5, 2.5]$.

Figure 4 shows the results that we obtained from our Python simulation using the same parameters from Chen and Kolokolnikov [1]. For simplification, we reduced the number of intermediate steps, but we were able to closely replicate the previous work. In the first row, $c = 0.15$, the swarm escapes completely. In the second row, $c = 0.4$, the predator catches up with the swarm but gets 'confused' as the swarm forms a stable ring around it. In the third row, $c = 0.8$, the predator catches up with the swarm; the swarm forms an unstable ring around it where regular oscillations are observed. In the fourth row, $c = 1.5$, the predator did not catch up with prey but complex periodic patterns can be seen. In the fifth row, $c = 2.5$, the predator 'catches' the prey and chaotic behavior is observed.

Having confirmed that our simulation worked correctly by successfully replicating the previous work, our next step was to explore the effects of multiple predators without predator-predator interactions.

B. Multiple Predators without Predator-Predator Interaction

The first extension to the previous work that we wanted to investigate was the effect of introducing multiple predators to the simulation (i.e. more than one predator). We first introduced more predators without predator-predator interactions. The main behavior we wanted to investigate was whether a greater number of 'slower' predators can catch a prey. In other words, we explored, for a same c value (short-range attraction gain), whether introducing more predators led to catching prey.

For this experiment, we used the model (5) and (6). We set the constant parameters to $N = 400$, $a = 1$, $b = 0.2$, $p = 3$, $r = 0.025$. The variable parameters were combinations of $c \in [0.15, 0.4, 0.8, 1.5, 2.5]$ and $M \in [1, 2, 3, 4, 5]$.

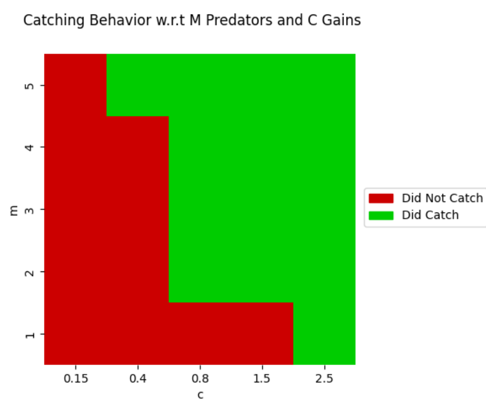

Fig. 5. Catching behavior for multiple predators without predator-predator interactions and with different c gains.

In Figure 5, we observe the catching behavior for multiple predators without predator-predator interactions and for different c gains. For one predator, there was only a prey catch at $c = 2.5$. For 2-4 predators, there were catches for $c = 0.8, 1.5, 2.5$. For 5 predators, there were catches for all c values except for $c = 0.15$. This shows that a greater number of predators does in fact lead to more catches for the same short-range attraction gain and with no interactions between the predators. This can be explained by analyzing the flocking behavior of multiple predators with no interaction in Figure 6. We observe that higher number of predators show more unstable confusion and chaotic confusion for different values of c. Both of these behaviors, chaotic confusion in particular, lead to more prey catches.

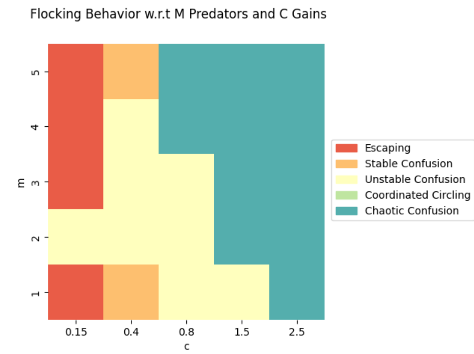

Fig. 6. Flocking behavior for multiple predators without predator-predator interactions and with different c gains.

C. Multiple Predators with Predator-Predator Interaction

The next extension that we investigated was the effect of multiple predators with predator-predator interactions. The main aspect we wanted to investigate were emergent behaviors from forces within the predator swarm.

We ran 256 experiments for this investigation and used the model (5) and (9). The constant parameters were set to $N = 400$, $a = 1$, $b = 0.2$, $p = 3$, $r = 0.005$. In the multiple predator predator-predator interaction model (Equation 9), the main 'tuning' gains are c, d, and e. Hence, the variable parameters were combinations of $M \in [1, 2, 3, 4, 5]$, $c \in [0.1, 0.2, ..., 0.8]$, $d \in [1.1, 1.0, ..., 0.4]$, and $e \in 1.5 - d$.

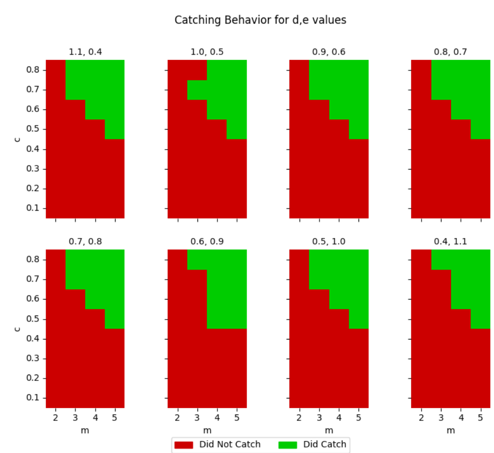

Fig. 7. Catching behavior for multiple predators with predator-predator interactions and different c gains.

Figure 7 illustrates how different combinations of d and e for multiple predators with different c values does not necessarily lead to more prey catches. All of the plots look very similar. However, the resulting behaviors from the different combinations of d and e clearly change, as shown in Figure 8. The main observation for the resulting behaviors is how, for combinations of higher d values and lower e values, the dominating behavior is coordinated circling. For lower d values and higher e values, the dominating behavior is unstable confusion, though we do see more stable confusion as well but no coordinated circling. d and e values that are closer to each other result in a more balanced mix of all behaviors.

Although for different ratios of d and e values there is a clear difference in flocking behaviors, the catching behavior across these experiments was very similar.

Fig. 8. Flocking behavior for multiple predators with predator-predator interactions and different c gains.

V. Conclusions

Our work showed that the introduction of additional predators within an environment can change the behaviors of the swarm drastically. Even changing the forces between agents can have a drastic impact on the behaviors of the swarm. The study of predator-prey interactions within simulation for swarm robotics provides valuable insights into adaptability and emergent behaviors of predator-prey swarms. Balancing adaptability and robustness is crucial for swarm systems, allowing them to effectively navigate changing environments. While challenges exist in translating simulations to physical implementations, this research field has the potential to advance our understanding of collective behavior and contribute to the development of advanced robotic systems.

A. Our Contribution

As outlined in section IV, we were able to determine that the introduction of multiple predators meant that it was easier for predators to get a kill, as well as altered their behaviors when changing the gains of Equation 7. We believe that we created a more accurate particle-physics based mathematical model that can be used to simulate swarm interactions of predators and prey.

B. Future Work

Though our work was short, we took some time to discuss our thoughts on future work that could be implemented into this model, or features that could used to ease the analysis process. First, using some form of machine learning to identify the behaviors as seen in Figure 3 in a more efficient manner. This would allow for an automated process that would not require humans to go through and characterize the behaviors, saving time, energy, and headaches. Second, we think it would be more realistic to introduce 2^{nd} order equations of motion (acceleration) into the model. This would make the movements of the predators and prey more realistic. Third, we would like to analyze the *catch rate* of the different parameters. We want to use the kill radius, defined in Section III-C, to eliminate any prey in the zone, then define a metric as to how long it takes to reduce the number of prey by a certain amount. This will allow us to qualitatively analyze the performance of the gains. Fourth, we want to perform differential analysis of the motion equations to determine steady state behaviors and stability of the system. Lastly, we think it would be interesting to investigate heterogeneous predators and prey, i.e. predators and prey with different maximum speeds/accelerations.

C. Concluding Remarks

Overall, our implementation of a particle-based mathematical model of predator-prey interactions within swarms has been instrumental in examining the intricate dynamics of these interactions. By manipulating the attractive and repulsive gains in our simulation, we have gained valuable insights into the nuanced behaviors exhibited by both predators and prey. Moreover, the introduction of additional predators has shed light on how the presence of multiple predators impacts the overall dynamics of the system. Our findings provided a deeper understanding of the underlying mechanisms at play in predator-prey interactions within swarm robotics.

We recognize that our current implementation is just the beginning of a broader journey in studying predator-prey interactions within swarm robotics. There are still many unanswered questions and unexplored aspects that offer exciting avenues for future investigation. In conclusion, our particle-based mathematical model of predator-prey interactions within swarms has provided a platform for in-depth analysis and understanding of the complex behaviors exhibited in these systems. The exploration of attractive and repulsive gains, as well as the introduction of multiple predators, has allowed us to unravel the dynamics of the interactions and gain valuable insights.

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