Swarming behaviour in predator-prey model

Ariana Kržan, Tina Brdnik, and Vito Levstik

Collective behaviour course research seminar report

November 13, 2024

Iztok Lebar Bajec | associate professor | mentor

Collective animal behavior, especially swarming in predator-prey dynamics, offers insights into survival strategies that emerge under evolutionary pressures. This report outlines the initial objectives and foundational concepts for simulating predator-prey. Inspired by previous work, we examine how survival pressures can drive emergent group behaviors in prey through reinforcement learning. We begin with an overview of related work, from classic rule-based models to more recent reinforcement learning approaches, highlighting advances that allow agents to adapt to changing environments. Our primary objective is to recreate a reinforcement learning-based model where predator-prey interactions lead to swarming and evasion behaviors. The model will then extend to include environmental obstacles and an additional species, enabling us to investigate the interplay between interspecies interactions and survival strategies.

Simulation | swarming behaviour | predator | prey

The sudden emergence of swarming behaviours in animals is one of the most striking examples of collective animal behaviour. These behaviours have been extensively studied for their implications for the evolution of cooperation, social cognition and predator–prey dynamics[1]. Swarming, which appears in many different species like starlings, herrings, and locusts, has been linked to several benefits including enhanced foraging efficiency, improved mating success, and distributed problem-solving abilities. Furthermore they are hypothesized to help with improving group vigilance, reducing the chance of being encountered by predators, diluting an individual's risk of being attacked, enabling an active defence against predators and reducing predator attack efficiency by confusing the predator. [2].

In this project we will be taking inspiration from the work of Li et al. (2023) and Olson et al. (2013) to explore how survival pressures can drive the emergence of swarming behaviour. The first goal will be to create a realistic simulation where both prey and predators learn to adapt through reinforcement learning based on their drive to survive. Modeling these interactions, we will observe how simple survival pressures can lead to evolution of more complex behaviours like flocking, swirling and edge predation.

Then, we will extend our research by evolving out existing model by introducing new environmental obstacles and new species to observe how interspecies interactions lead to new survival strategies.

Related work

The modeling of swarming behavior has evolved from foundational rule-based frameworks to more sophisticated reinforcement learning (RL) approaches, with intermediate advances in topological and vision-based models that add realism to agent interactions.

Rule-Based models. Early models of swarming relied on static interaction rules to simulate basic group dynamics. Aoki's Zone Model (1982) introduced three interaction zones-repulsion, alignment, and attraction-where agents adjust their behavior based on proximity to neighbors [3]. Later, Vicsek's Model (1995) and Reynolds' Boids Model (1987) introduced basic alignment rules (and in Reynolds' case, also cohesion and separation) to generate coordinated group movement [4][5]. Although effective in modeling simple swarming behaviors, these models rely on fixed rules that limit agents' ability to adapt dynamically to changing environments or threats.

Topological and Vision-Based Extensions. Topological and vision-based models improved realism by adding sensory and neighbor-based constraints. Hemelrijk & Hildenbrandt (2008) introduced a perception model where agents respond only to neighbors that are visible within a variable radius, adjusted by local density, stabilizing cohesion across varied densities [6]. Kunz & Hemelrijk (2012) further refined this approach by incorporating visual occlusion, where agents respond only to visible neighbors, simulating real-world sensory limitations [7]. While these models increase biological realism, they remain rule-based and lack the flexibility of adaptive RL models.

Here goes significance statement.

Simulation | swarming behaviour | predator | prey

Advances in RL-Based Models. Reinforcement learning has enabled a significant leap in modeling swarming behaviors by allowing agents to learn and adapt based on environmental feedback rather than relying on fixed rules. RL models produce dynamic, emergent behaviors like flocking and evasion, closely mimicking natural adaptive responses to survival pressures.

- Li et al. (2023): In this RL-based predator-prey model, prey agents develop swarming behaviors by maximizing survival rewards and minimizing capture penalties [2]. Prey adaptively form cohesive groups and evade predators, learning these behaviors through experience rather than pre-set alignment rules.
- Olson et al. (2013): Olson and colleagues focused on predator confusion, where prey learn to cluster, reducing individual predation risk by confusing predators [1]. This model highlights RL's capability to foster adaptive, emergent behaviors in predator-prey dynamics.
- Lowe et al. (2017): The Multi-Agent Deep Deterministic Policy Gradient (MADDPG) algorithm enables agents to learn in mixed cooperative and competitive environments, making it ideal for systems with multiple interacting species [8]. MADDPG supports complex, dynamic environments by allowing agents to optimize strategies in both cooperative and adversarial contexts, such as predators and prey with differing objectives.

Methods

Our proposed methodology aims to simulate swarming behaviors in a predator-prey environment using reinforcement learning (RL). We will define and test a RL-based model where agents, such as prey, predators, and possibly a new species, interact within a two-dimensional space. The goal is to observe how different pressures and interactions influence collective behaviors like swarming, evasion, and strategic movement.

Environment Setup. The simulation will take place in a 2D environment with open and confined spaces. Later on we wish to place random obstacles, which will be distributed across the space to create a complex and realistic setting that challenges the agents to adapt their movement and coordination.

We will apply the perception and action models from Li et al. (2023) [2] to guide agent interactions in the simulation.

- **Perception Model**: Each agent detects others only within a specified range and limited to a maximum number of nearby agents, simulating real-world sensory limitations.
- **Action Model**: Agents adjust their movement through forward propulsion and directional changes, governed by RL policies that optimize goals like survival and prey capture.

Agent Types and Behavior.

- **Prey**: These agents aim to survive by avoiding predators and moving as a group.
- **Predators**: Predators are designed to pursue and catch prey.
- **New Species**: We may introduce a third type of agent, such as a neutral species, scavenger or competitor, which will have its own survival or resource-based objectives.

Reinforcement Learning Framework.

- **Algorithm**: We plan to use the Multi-Agent Deep Deterministic Policy Gradient (MADDPG) algorithm.
- **Reward Structure**:
  - **Prey**: Rewarded for survival over time, with penalties for being caught.
  - **Predators**: Rewarded for capturing prey, with penalties for colliding with obstacles.
  - **New Species**: Rewarded based on interactions like resource competition or cooperation with other agents.
- **Training Setup**: Agents will be trained through episodic simulations, allowing them to learn and adapt from each episode's interactions. We will vary conditions to observe how changes influence learned behaviors.

Results

Even though we currently don't have any results, we can outline what we anticipate to achieve. One of the results will be a simple model that is a recreation of Li et al. (2023) model in python. It is expected to model the development of swarming behaviours. We have already extracted their code and have successful ran it. We intend to compare our results with the article.

After that, we will build upon our existing model by adding new obstacles and interspecies interactions.

Discussion

Though we just started working on the project, we have already encountered some issues when trying to run the code of our main article. We managed to contact the original authors and they were quick and happy to help so as of right now, we are happy to report we got the code working and running.

We acknowledge that we have set ambitious goals, especially by introducing a new species into the mix. We anticipate a lot of new issues will arise through the semester, however we are excited to challenge ourselves and we are determined to learn from the process no matter the outcome.

Initially this project began with just two people working on it, but due to the complex nature of the project, we have joined forces with another group of just one member. This will enable us to work on the assignment more efficiently and have easier time achieving our goals.

CONTRIBUTIONS. AK worked on introduction, expected results and discussion, TB worked on related work, VL worked on abstract and getting original model to work.

1. Olson RS, Hintze A, Dyer FC, Knoester DB, Adami C (2013) Predator confusion is sufficient to evolve swarming behaviour. *Journal of The Royal Society Interface* 10(85):20130305.
2. Li J, Li L, Zhao S (2023) Predator–prey survival pressure is sufficient to evolve swarming behaviors. *New Journal of Physics* 25(9):092001.
3. AOKI I (1982) A simulation study on the schooling mechanism in fish. *NIPPON SUISAN GAKKAISHI* 48(8):1081–1088.
4. Vicsek T, Czirók A, Ben-Jacob E, Cohen I, Shochet O (1995) Novel type of phase transition in a system of self-driven particles. *Physical Review Letters* 75(6):1226–1229.
5. Reynolds CW (1987) Flocks, herds and schools: A distributed behavioral model. *SIGGRAPH Comput. Graph.* 21(4).
6. Hemelrijk CK, Hildenbrandt H (2008) Self-organized shape and frontal density of fish schools. *Ethology* 114(3):245–254.
7. Kunz H, Hemelrijk CK (2012) Simulations of the social organization of large schools of fish whose perception is obstructed. *Applied Animal Behaviour Science* 138(3):142–151. Special Issue: Living In Large Groups.
8. Lowe R et al. (2017) Multi-agent actor-critic for mixed cooperative-competitive environments. *Proceedings of the 31st International Conference on Neural Information Processing Systems*.