Investigating desirability of boid like behaviours in a predator/prey simulation

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Computer simulation is used to find conditions which encourage the emergence of 2d boid-like behaviours in prey through natural selection. This is achieved through an evolutionary simulation of behaviours with predator and prey agents in Unity. The method finds some examples of boid behaviours genetic behavioural encouragement being dependant on prey vision range. It does not find conclusive evidence supporting a dependence on prey population.

I. INTRODUCTION

Attempts to reconstruct observed flocking behaviour in wildlife have led to the construction of multi-agent boid models. The base model for boid-like behaviour involves 3 rules for each agent in a multi agent system. The desired direction of movement is determined through observing other neighbouring agents in the system.

- Firstly, they must attempt to align themselves with other agents.
- Secondly, they must avoid collisions with these neighbouring agents.
- Finally they must attempt to move towards the central point of the locally observed agents.

[1] Each of these behaviours have since been measured and observed in real behavioural systems. One study found all three behaviours in tadpoles, with varying rates of appearance depending on the vision range of the individuals.[2] It has been demonstrated mathematically that this can be beneficial for the survival of an individual in a situation with predators under specific conditions, and that boid behaviour is more encouraged when the predator has greater vision.[3]

Variations to the base set of boid rules exist, including 3d variants. 2d variants, and variants altering speed in an attempt to more closely match observed behaviour of flocks in different scenarios.[4]

I intend to investigate the genetic encouragement of these behaviours over time under specific conditions for a two-dimensional environment with a predator/prey simulation. Evolutionary algorithms are based on natural selection in animals. [5] Information from the best performing agents are passed down to the following generation of agents. Only successful agents are allowed to reproduce. This is achieved through several steps.

- Agents perform actions in an environment with a task
- Agents are scored based on their performance at a task
- Successful agents reproduce for the next generation of agents

Relevant data in an agent is referred to as a chromosome and is often represented as a bit-string. This is further subdivided into genes which hold an individual component of information. This reproduction is typically a combination of mutation and crossover. [6] Crossover involves creating the child chromosome from some split of two parent chromosomes. Mutation involves changing random genes throughout the child chromosome. In the case of a bit-string, this would mean the flipping of random bits in the chromosome.

In this paper I use probabilistic behaviours on agents to simulate prey, and simple hunting behaviours on other agents to simulate predators. The prey agents must avoid predators and consume randomly placed food to survive. Prey in the model improve the probability of favourable behaviour over time through a genetic algorithm. I observe the behaviour probabilities over time to find which behaviours are most favourable and which are entirely bred out as the model approaches a stable state. It has previously been found that herding behaviour can be evolved solely through evolutionary simulation.[7] In this paper, I explore whether 2d boid-like behaviours more heavily are encouraged for survival in situations with more predators, and investigate the effect of prey vision range on this.

II. METHOD

A. Environment

All agents have physical representations in a 3 dimensional space which only allows for 2 dimensional movement. Resources are placed randomly within an area at specific time intervals, and prey must compete with their neighbours to get these resources, which encourages some exploration. Ever 2 seconds, 7 resources spawn at random locations within a 15*15 unit area.

Direct interactions between agents can happen at a distance of 1.2 units. these interactions include eating, avoiding nearby agents during boid behaviour, and predator agents killing prey. (1)

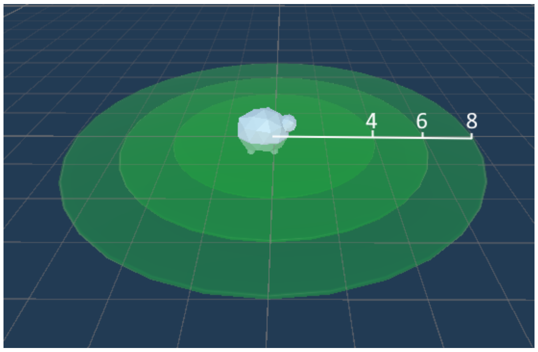

FIG. 1. Visual demonstration of unit ranges next to a prey agent

B. Agents

There are two types of intelligent agents in the simulation, prey agents and predator agents. Prey agents move at a constant speed of 1 unit per second. They have a range of vision in all directions(1), in which they are able to detect neighbouring prey, predators and grass. They have a collider volume preventing them from entering the same space as another agent. They may only alter their angle. This is constrained, and the angle of movement is determined through the midpoint of their current direction of movement and their intended direction of movement. This prevents the agents from being able to instantly face the opposite direction. Each prey agent has three mechanisms for causing death, and their removal from the simulation. The first is starvation, from failing to find resources for 25 seconds. This is a mechanism for preventing the size of the population from growing exponentially and allows the model to maintain a stable prey population. it also rewards exploration. The second is from old age, upon reaching an age of 50 seconds, the agent obtains a chance of death at each time interval. This is important to ensure success of the genetic algorithm so that parents cant repeatedly out-compete their children. The chance of death at each time interval is 2/1000. This randomness helps discourage unusual instability from a large change in the environment due to simultaneous mass death. The final method for the prey to die is through entering close proximity to a predator agent.

Predator agents are simpler. They have a maximum speed of 3 units per second, they have full control of their intended direction of movement and they have a vision range of 6 units. Prey agents cannot be destroyed during the simulation. They are always aware of the central position of the prey to ensure they are always capable of finding the population when hunting.

C. Reproduction

Once prey reach a certain age they can reproduce. This age is chosen as 25 seconds such that they are required to have eaten at least once before they reproduce. This serves as replacement for a fitness function by only selecting well fed agents and those which have survived predators for reproduction. Upon reproduction, a new agent is created whereby the chance of it choosing each behaviour at a given time step is decided through random variance from the probabilities its parent agent had. The genes of the prey agents are floats, representing the weightings for likelihood of entering specific predetermined behavioural patterns at each time-step in the simulation of the individual's behaviour. The chromosome consists of several genes, one representing random movement, one for boid behaviour and one for movement towards a central location in the habitable environment. Chance for reproduction at a given timestep is 3/1000. This was chosen experimentally to be a value which would allow the prey population to easily replenish. Due to the simple chromosomes, I use mutation without crossover. This should allow a potential for groups with different survival strategies to exist within the same simulation, and for greater exploration of the behaviour space. Here, the fitness function is replaced by death of the agent before reproduction.

D. Prey action selection mapping

1. *Priority actions*

Prey have two behaviours that take priority over their genetic behaviours in order to encourage survival of the prey population. The first priority is a behaviour to avoid predators. During this behaviour, the prey agents will calculate the average position of predator agents within their vision range and and take action to attempt to move in the opposite direction. The next behaviour takes place only if the prey have not consumed resources in the last 18 seconds. They will take action to attempt to move towards a randomly chosen resource within their vision range.

2. *Probabilistic action selection*

If the above conditions are not met, the prey has probabilistic action selection based on the values of the floats within it's chromosome . Value ranges are created dependant on the values of the floats in each gene, and a random number is generated within the same range which determines the action the agent takes.

State 1- The behaviour represented by the first gene chooses a random location near the prey, and the prey will take action to move towards that location.

State 2- The behaviour represented by the second gene is boid behaviour. The agent will take an average of the following three directions.

- Movement away from a nearby prey. This direction is not included in the calculation if the nearest prey agent is further away than interaction range.
- The average direction of movement of all other prey agents within the agent's vision range.
- The average position of all other prey agents within the agent's vision range.

State 3- The third behaviour causes the agent to take action to move towards a location in the centre of the area where resources can spawn. This behaviour is chosen to encourage the stability of the simulation while it finds an equilibrium such that the agents maintain some proximity to their food sources.

E. Predator action selection mapping

Predator agents are simpler agents, and have 2 states.(2)

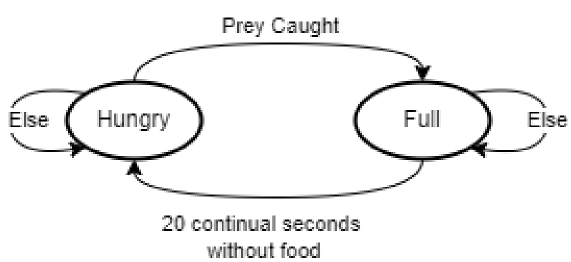

FIG. 2. State relationship diagram for wolf behaviour

Hungry state: They will move towards the central point of the prey. If prey exist within their vision range of 6, they will choose one at random and move towards the position of that prey agent. They move faster than the prey agents to make hunts successful, with a speed of 18. Upon catching prey, they enter the full state. Full state: A predator in the full state will move away from the central point of the group of prey agents. They will move significantly slower, with a speed of 6, however will still kill prey agents who walk into them. A predator in the full state will enter the hungry state again after 20 seconds.

III. RESULTS

All time recorded is in seconds, and behaviour weightings show the average values of each behaviour state across all surviving prey agents. State 1 controls random movement, State 2 controls boid behaviour, and State 3 controls recall behaviour to a central location. In all occasions, prey population reached its stable capacity in its respective environment within 500 seconds.

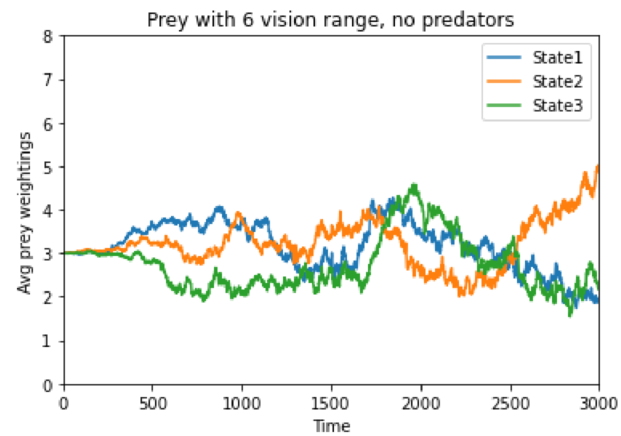

FIG. 3. Prey with 6 vision range and without predators- Prey successfully maintained population over long time scale, a stable state existed for short time period after 1650 seconds.

In the case with a prey vision range of 6 and no predators, (3), a stable state was reached as measured between 1400 and 1650 seconds. –

	Avg weighting	Rel. probability	Variance
State 1	3.45	0.37	9.99 $\times 10^{-3}$
State 2	2.66	0.28	2.39 $\times 10^{-2}$
State 3	3.31	0.35	3.94 $\times 10^{-2}$

–

Prey with 2 vision range and 7 predators led to unstable population and prey extinction.

In the case with a prey vision range of 4 and 7 predators, (4), a stable state was reached as measured between 1000 and 1500 seconds. –

	Avg weighting	Rel. probability	Variance
State 1	3.49	0.34	1.81 $\times 10^{-2}$
State 2	2.96	0.29	1.41 $\times 10^{-2}$
State 3	3.78	0.37	2.16 $\times 10^{-2}$

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In the case with a prey vision range of 6 and 7 predators, (5), a stable state was reached as measured between 1000 and 1250 seconds. –

	Avg weighting	Rel. probability	Variance
State 1	4.28	0.44	4.57 $\times 10^{-2}$
State 2	2.51	0.26	1.20 $\times 10^{-2}$
State 3	3.00	0.30	1.81 $\times 10^{-2}$

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In the case with a prey vision range of 8 and 7 predators, (6), a stable state was reached as measured between 1700 and 1950 seconds. –

	Avg weighting	Rel. probability	Variance
State 1	0.66	0.07	4.28 $\times 10^{-2}$
State 2	5.79	0.59	4.16 $\times 10^{-2}$
State 3	3.37	0.34	4.05 $\times 10^{-2}$

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Prey with 10 vision range and 7 predators led to unstable population and prey extinction

In the case with a prey vision range of 6 and 5 predators, (7), a stable state was reached as measured between 1750 and 2000 seconds. –

	Avg weighting	Rel. probability	Variance
State 1	3.44	0.39	4.67×10^{-3}
State 2	1.74	0.20	2.80×10^{-2}
State 3	3.55	0.41	1.32×10^{-2}

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In the case with a prey vision range of 6 and 6 predators, (8), In this simulation, no stable state was found.

IV. EVALUATION

For the purposes of analysis, I define a stable behavior state to be one in which each behaviour has a variance of less than 0.05 over a range of at least 250 seconds.

The simulations led to unstable behaviour states in many conditions, however the results demonstrate that this method is capable of finding some temporarily stable states under the right conditions.

When measuring the effect of variation in vision range, a prey population could not be maintained for a prey vision range of 2 or 10. In the case with range 2, Prey agents were unable to find food and starved. In the case where prey had a vision range of 10, their avoidance of predators often led to leaving the survivable area and death through starvation. The prey population survived in the simulations with seven predators for four, six, and eight vision range. (4)(5)(6) In each of these, a period in time could be identified meeting my definition for stable behaviour. Amongst these, boid behaviour was only encouraged with 8 vision range, where boid behaviour has a probability of 0.59 population during the period of stability. This supports the expectation that boid range should be more prevalent with vision range.

Due to the limits of stability in simulation, it is hard to draw conclusions from the simulations with a set prey vision range of 6, and varying predator population sizes. Only the simulations with 5 and 7 predators were able to meet my definition of a stable state.(5)(7)(8) Between these, the instance with the larger predator population favours boid behaviour compared to the simulation with lesser predator population. In both however, these rates are still low compared to other behaviours with probability 0.26 and 0.2 respectively. In the situation without and predators, the stable state was reached with boid behaviour achieving a probability of 0.28(3). There is therefore insufficient data to support a claim that increasing predator population size increases the relative probability of behavioural evolution towards a boid state in the prey population.

V. CONCLUSION

The simulation proved to produce stable results too unreliably to draw many meaningful conclusions and for the conditions to me easily altered and tested. The results did demonstrate one scenario in which boid behaviour was encouraged heavily through genetic simulation and a stable state was found. Therefore it is clearly possible have conditions which encourage such behaviour genetically, and these conditions existed with a high rate of predators. This could support the idea that predators drive evolution towards boid behaviours. The findings with respect to the vision range of the prey were consistent with previous research, and results were highly dependant on fine tuning this value.

A. Improvements

1. Normalising the chromosome

With weighted choice for behaviour, the effect of a change in the weighting is comparative to the size of the other weightings. Occasionally, the most successful agents from the initial population had randomly received higher numbers for their genes. This led to a population with higher average values across all individuals and meant that similar changes to the gene through mutation had a smaller impact on the behaviour than in those with a lower average value. This prevented fine tuning of the scale of mutation across all scenarios. A solution would be to present all the weightings as a normalised vector with a much smaller range for genetic mutation.

2. Improving Predator behaviour

The implementation of the predators left the possibility for them to remain stationary if they reached the centre of the population of the prey without successfully finishing a hunt. This should be addressed in a revision of the experiment since in some tests, it led to population death through pushing the prey away from the food sources.

3. Introduction of crossover

There is potential for stability of the models to be increased through use of crossover, and therefore I would not recommend repeating a similar experiment without implementation.

B. Further research

This experiment could be easily extended to explore any range of behaviour patterns and was reduced to three for simplicity. Other models for behaviour could be experimented with.

The prey agents in the simulation had many layers of randomness which could be removed for a more precise mathematical model at the expense of proximity to natural behaviours in animals. The benefit to this is that a more traditional model should behave more consistently and be easier to tune.

A looping environment would also be an effective way of reducing prey population death but would require some significant changes to implementation of predators.

Another notable extension to this project would be to see if the results repeat for agents who can move through 3 dimensions. This would be more comparable to much existing literature which focuses on birds and fish which move through a 3d environment. [3] [2]

[1] Craig reynolds: Flocks, herds, and schools: A distributed behavioral model.

[2] L. C. Katz, M. J. Potel, and R. J. Wassersug, Structure and mechanisms of schooling intadpoles of the clawed frog, xenopus laevis, Animal Behaviour **29**, 20 (1981).

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[7] C. R. Ward, F. Gobet, and G. Kendall, Evolving collective behavior in an artificial ecology, Artificial Life **7**, 191 (2001).

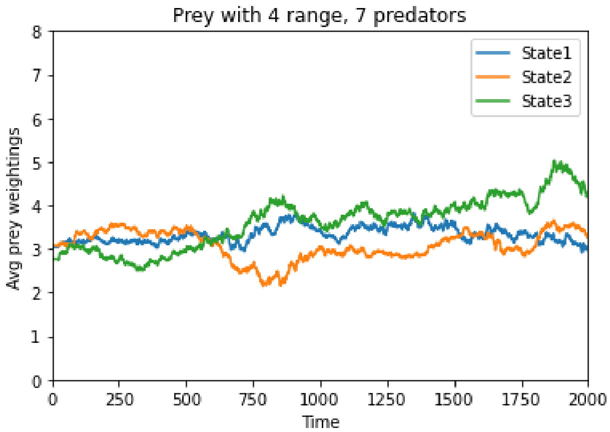

FIG. 4. Prey with 4 vision range and 7 predators- A stable condition was reached over many generations with boid behavior as the least common behaviour. This eventually fell back into instability.

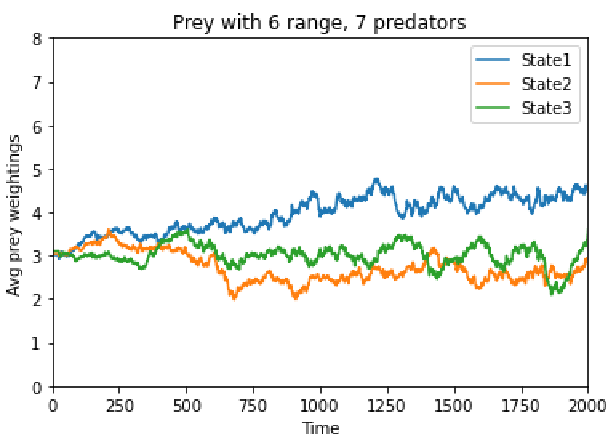

FIG. 5. Prey with 6 vision range and 7 predators- stable condition was reached over many generations with random walking as the prevalent behaviour. Boid behaviour stayed consistently unfavourable but not notably so.

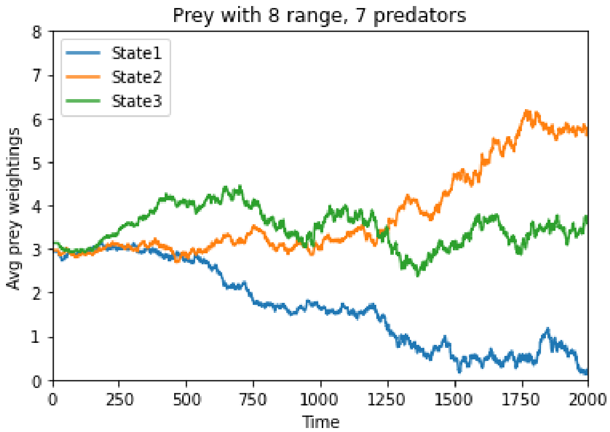

FIG. 6. Prey with 8 vision range and 7 predators- a stable condition was reached over many generations with boid behaviour as the prevalent behavior and random behaviour heavily discouraged

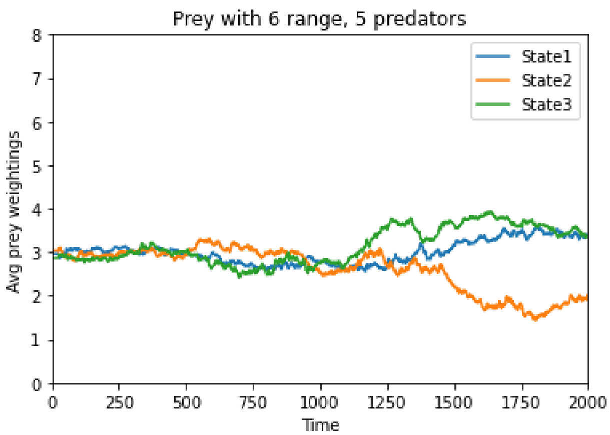

FIG. 7. Prey with 6 vision range and 5 predators-Boid behaviour was found to be notably unfavourable compared to the other two behaviours and appears to be reaching stability.

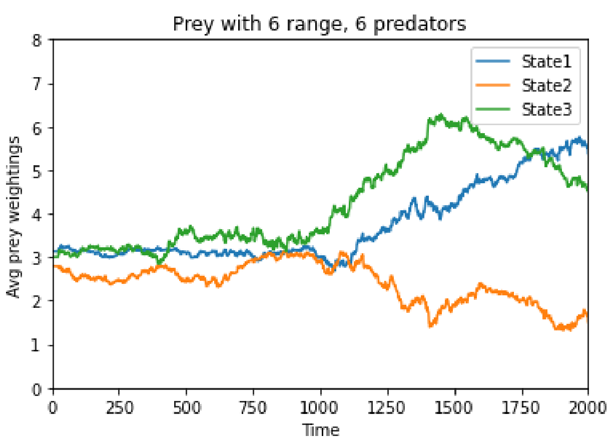

FIG. 8. Prey with 6 vision range and 6 predators-Boid behaviour was found to be notably unfavourable compared to the other two behaviours though stability is unclear.