

Simulating Ant Colonies To Investigate How Minor Worker vs Major Worker Ant Distributions Affect Colony Energy

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Abstract

Ant colonies have the unique ability to dynamically search the terrain surrounding their environments, detect and retrieve sources of food. This is an emergent behaviour that has been well well explored by a variety of past studies [1] often with a focus on examining the way that paths to and from food sources are created and organised. In reality, many species of ants have a number of different castes of ants within their ranks [2]. This study examines what affect different distributions of two castes of ants in particular – the *minor*- and *major-worker* ants – within a colony have on that colony’s overall health when faced with differing conditions.

Ant colonies are simulated in Matlab on train that has been descritised into chunks, and food is spawned randomoly throughout the terrain. Ant colonies with differing ratios of simulated minor and major worker ants are created, and their success – as measured by [MEASUREMENT HERE].We found that [FINDINGS HERE] These findings indicate that [INSIGHT INTO ANTS HERE], indicating that a mix of major and minor workers is the most suitable – with the minor workers excelling at [SOMETHING?] while the major workers [DO SOMETHING ELSE], as seen in nature [CITE THIS ACTUALLY HAPPENING - Or, I guess don’t if it doesn’t really happen and just state that our model was wrong.]

1 Introduction and Background

Ants are *eusocial* creatures, meaning that they possess the highest level of organisation that any social species of animal can possess[3, 4]. Behaviour allows them to perform incredible feats as a whole, even when individually each ant has very little actuation over its environment. One such example of this is an ant colony’s ability to forage for food from its surrounding area, while avoiding obstacles and successfully navigating changes in its environment. This ability in itself has been examined a significant amount in past research[5, 6], and has even lead to algorithmic methods inspired by the behaviour being developed to solve problems faced in areas of computer science, such as those similar to the *travelling salesmant problem*[7, 8].

Another characteristic of eusocial creatures – and the focus of our own investigation – is the separation of groups within the colony into differing *castes* that exhibit specialized behaviour, making them more fit for certain types of jobs over others of their colony[4]. Ants in particular are often divided into up to four differing casts: Queens, Minor Workers (Workers), Major Workers (Soldiers) and Drones[9, 10]. According to work performed by W. R. Tschinkel in his journal article on the distribution of worker ant populations within colonies, *Colony growth and the ontogeny of worker polymorphism in the fire ant, Solenopsis invicta** [11], minor workers typically make up 65% of the worker population within a mature colony with major workers making up just 35%. Tschinkel measured these stable distributions only in more mature colonies (colonies over six years of age), in particular, in *fire ant* colonies.

Our experiment is interested in the area of finding the ratio of minor to major worker ants that has the most positive impact on an ant colony’s ability to thrive within a changing environment. It will revolve around an agent based simulation of ant foraging behaviours around a nest in an environment where food is randomly spawned to be consumed by the colony, and the colony can produce two differing types of ants representing the major and minor worker ants.

Agent based models are models, typically of natural systems, that simulate the system they are modelling through the use of individual *agents*. As opposed to mathematical models that aim to simulate a system by generalizing the behaviour of potentially many components into few mathematically described expressions (such as population over time, or growth rate with food consumed), agent based models simulate each component individually and the interactions between them[?], allowing them to simulate potentially unexpected emergent behaviour that is hard to describe using mathematical approaches – this makes them particularly useful when evaluating complex systems that exhibit strong emergent behaviour such as the flocking of birds or, as in our case, the retrieval of food exhibited by ant colonies.

A number of past studies have examined the way that ant colonies search their surrounding areas to locate and retrieve food [5, 6]. Often the these studies focus on simulating ant colonies to apply the emergent behaviour that they exhibit to solve abstracted technical problems [7, 8], with seemingly a smaller number of past works focusing on simulating ant colony behaviour as it is seen in nature [5]

The 2004 work by Vittori et al.[5] examined the way that ants navigate their environment, using trails of deposited pheromones which attract other ants from the colony toward food or back to the colony. This work in particular was of interest to us, as it evaluated the results of the model by comparing them to real ants in a number of experiments. Vittori et al implement a very reduced model for their simulation that allowed each ant to only allowed to move through a relatively small graph of various positions, with each node having a reference to a real-world counterpart and ant behaviour when deciding which path to take not only being based on pheromone depositions but also partially on the angle at which the ant would have to move through to get to the next node. The model also introduced restrictions to certain actions that the ants could take, such as the a maximum number of U-turns an ant could perform on a long branch, allowing the ants a way to backtrack in a similar way to observed behaviour in real ants but not allowing them to get caught in a repeated loop of U-turns.

Panait et al. introduces the concept of a dual-pheromone system in “Ant Foraging Revisited” [6] demonstrating the use of a two-pheromone system allowing for learning of paths to both food sources and the colony’s nest. This is an alternative to many previous systems that used ingrained knowledge within each ant or the environment itself to direct returning ants toward the nest. It appears to have the benefit of better mirroring real-world ants, but does increase total the complexity of the system. Comparing the dual-pheromone method explored by Panait et al.[6] with the more direct methods of behaviour coding described by Vittori et al.[5], it can be seen that there benefits to both systems. Vittori et al. often choose to simplify ant behaviour, resulting in faster models that still appear to reflect behaviour exhibited in the real world, whereas Panait et al. opt for more realistic real-world behaviours based on the assumption that the ants have no intrinsic knowledge of their environment.

However, there are examples of ant species such as desert ants that can find their way back to their nest seemingly using ‘natural pedometers’[?], lending support to the idea of modelling a system in which the agents know intrinsically information about themselves and the position of their nest.

2 Methodology

2.1 System Description

At the highest level our ABM consists of one agent, Ants, and an environment that contains their colony, food and then the pheromones that the ants leave behind. This high level behaviour is described by the state diagram Figure 1 in Appendix A. We have modelled two types of ants, major workers and minor workers. These are called workers, for major workers, and scouts, minor workers, in this project’s code and some of the diagrams.

The system aims to simulate colonies of ants as they forage for food in a 2-D environment. Each colony of ants exists as a single spawn point out of which ants leave to look for food. The state diagram in Figure 2 found in Appendix A details this behaviour. Each tile contains a value for the strength of food pheromone for each colony. Ants can move from tile to tile to follow pheromone trails towards food. If an ant cannot see a food pheromone trail then they will explore away from the nest for new food sources or food pheromone trails to follow. As can be seen in Appendix A Figure 4 Ants will reinforce a pheromone trail when they return to the nest with food. Over time these pheromone trails will decay. This is described by Robinson’s journal article [12] which details the decay rates of varying types of pheromones in ants’ foraging networks. Ants will only reinforce those food pheromone trails that they find food at the end of.

2.2 Assumptions

An assumption made was to not model factors that affect ant speed. One example is ant encounters, this being where two ants move over each other and cause a slowdown. The reasoning for this was that as according to one study ‘direct or interaction effects, has a much smaller effect on walking velocity than does body size’ [13], therefore the speed of an ant is determined entirely by their body size, which is given as the most important factor. Another example is ant size, we are assuming that ants of all sizes move at the same rate.

Additionally, although ants were modelled to have continuous locations, the environment is grid based and so pheromone trails were located by their tile position. The purpose of this model is that it finds statistical patterns based on the proportion of scout/worker ant populations in each colony, therefore, it is not important that the entire system is modelled in a way that is physically accurate on a ground level, rather that the simulation provides results which are statistically representative of ant colony behaviour.

The properties of food were assumed. The two main assumptions that were made here were the generation rate of the food and the decay rate of the food. The generation of the food was done by starting with n tiles of food and then generating n tiles of food in random places in the environment every n iterations. The decay rate of the food was not implemented so food was assumed to exist from creation until it was used up by the Ants.

Another, food based, assumption that was made was that food remained in the same place as it was generated.

2.3 Experimental Setup

2.3.1 Ants

Table 1: This table details the parameters used for each ant in our experimentation

Ant Type	Speed (mm s^{-1})	Maximum Energy Level	Energy Use Per Iteration
Major Worker	51.9	600	4
Minor Worker	51.9	150	1

2.3.2 Experimental Values

As detailed in the introduction with reference to W. R. Tschinkel’s journal [11], minor workers typically make up 65% of the worker population and major workers make up just 35%. Our project is investigating how minor worker vs major worker distributions affect colony energy hence we will be changing the values used in terms of the perc

2.3.3 Experiment Description

2.3.4 Repeatability

Simulation length - 1500 iterations
 Ant Speed - 51.9 mm s^{-1} [13]
 Ant Energy usage.
 Tile Size - 3.1m x 3.1m
 Environment Size - 50 tiles x 50 tiles

Iteration length - 1 minute Therefore we are simulating the colony behaviour for just over a day, 25 hours.

3 Results

4 Discussion

5 Conclusions

References

- [1] S. Camazine, J.-L. Deneubourg, N. R. Franks, J. Sneyd, and G. Theraulaz, *Self-Organization in Biological Systems*. Princeton studies in complexity, Princeton University Press, 2003.
- [2] “Caste Terminology - AntWiki.”
- [3] E. Wilson, *The Insect Societies*. Jan. 1971.
- [4] D. Hadley, “What Are Social Insects?.”
- [5] K. Vittori, J. Gautrais, A. F. R. Arajo, V. Fourcassi, and G. Theraulaz, “Modeling Ant Behavior Under a Variable Environment,” in *Ant Colony Optimization and Swarm Intelligence*, Lecture Notes in Computer Science, pp. 190–201, Springer, Berlin, Heidelberg, Sept. 2004.
- [6] L. A Panait and S. Luke, “Ant foraging revisited,” Jan. 2004.
- [7] M. Dorigo, M. Birattari, and T. Stutzle, “Ant colony optimization,” *IEEE Computational Intelligence Magazine*, vol. 1, pp. 28–39, Nov. 2006.
- [8] Y. Zhang, Z. l. Pei, J. h. Yang, and Y. c. Liang, “An Improved Ant Colony Optimization Algorithm Based on Route Optimization and Its Applications in Travelling Salesman Problem,” in *2007 IEEE 7th International Symposium on BioInformatics and BioEngineering*, pp. 693–698, Oct. 2007.
- [9] “Ant Family Castes.”
- [10] “Castes of ants.”
- [11] W. R. Tschinkel, “Colony growth and the ontogeny of worker polymorphism in the fire ant, *solenopsis invicta*,” *Behavioral Ecology and Sociobiology*, vol. 22, pp. 103–115, Feb 1988.
- [12] E. J. H. Robinson, K. E. Green, E. A. Jenner, M. Holcombe, and F. L. W. Ratnieks, “Decay rates of attractive and repellent pheromones in an ant foraging trail network,” *Insectes Sociaux*, vol. 55, pp. 246–251, Sep 2008.
- [13] M. Burd and N. Aranwela, “Head-on encounter rates and walking speed of foragers in leaf-cutting ant traffic,” *Insectes Sociaux*, vol. 50, pp. 3–8, Feb 2003.

A Appendix Figures

This section of the Appendix contains the state diagrams that are required for the Methodology section but are too large to include in the actual body of the report.

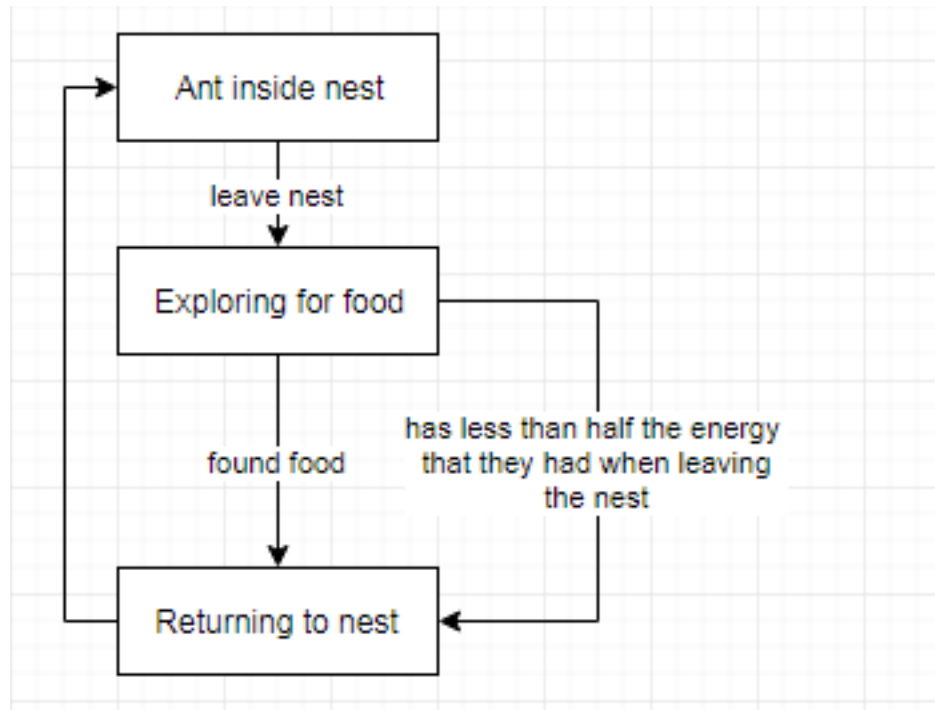


Figure 1: High Level State Diagram for the Ant

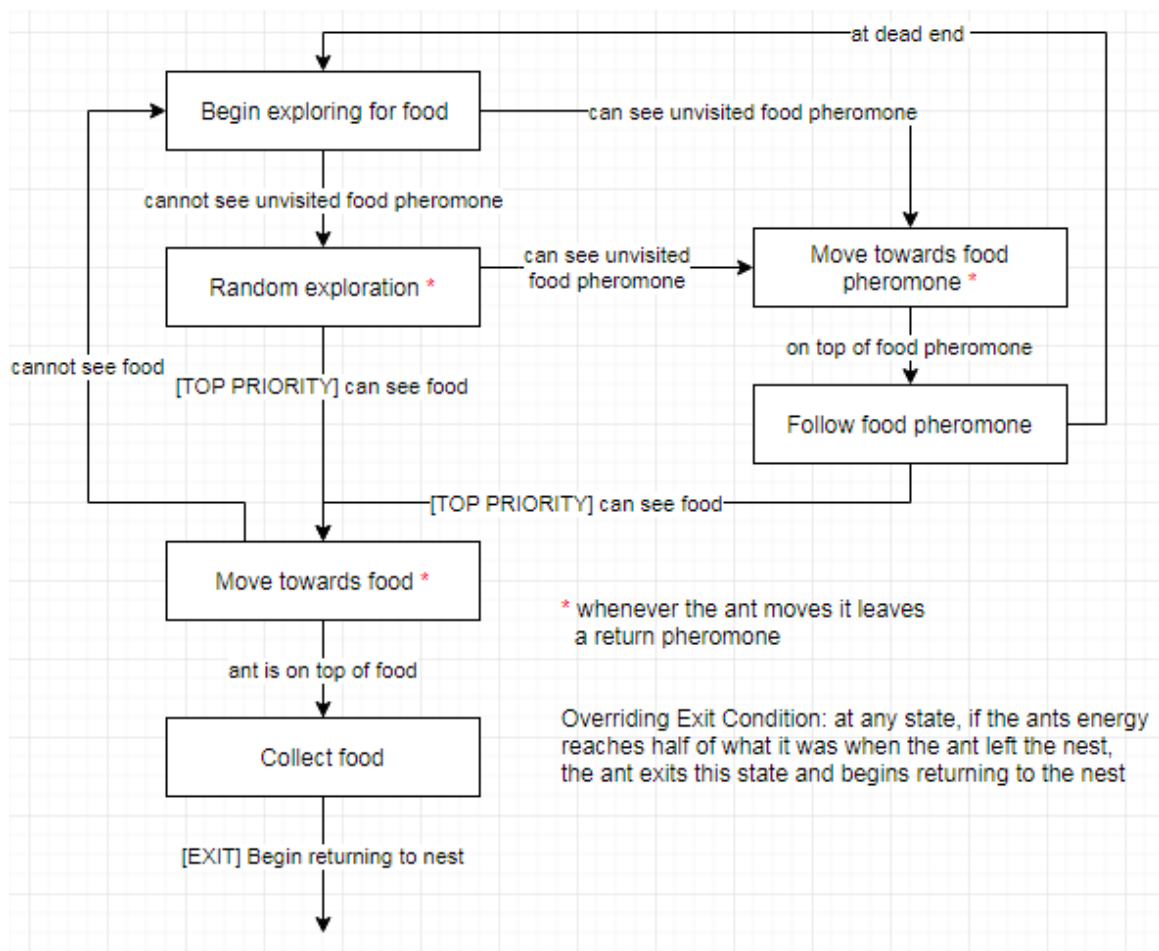


Figure 2: State Diagram for the Ant Exploring

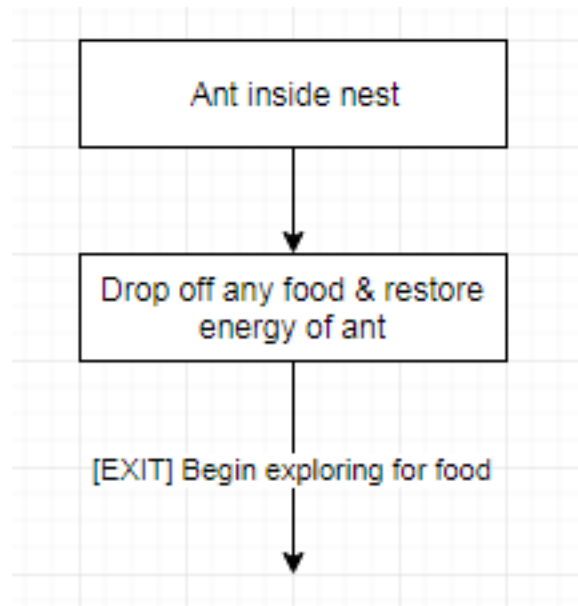


Figure 3: State Diagram for the Ant interacting with the nest

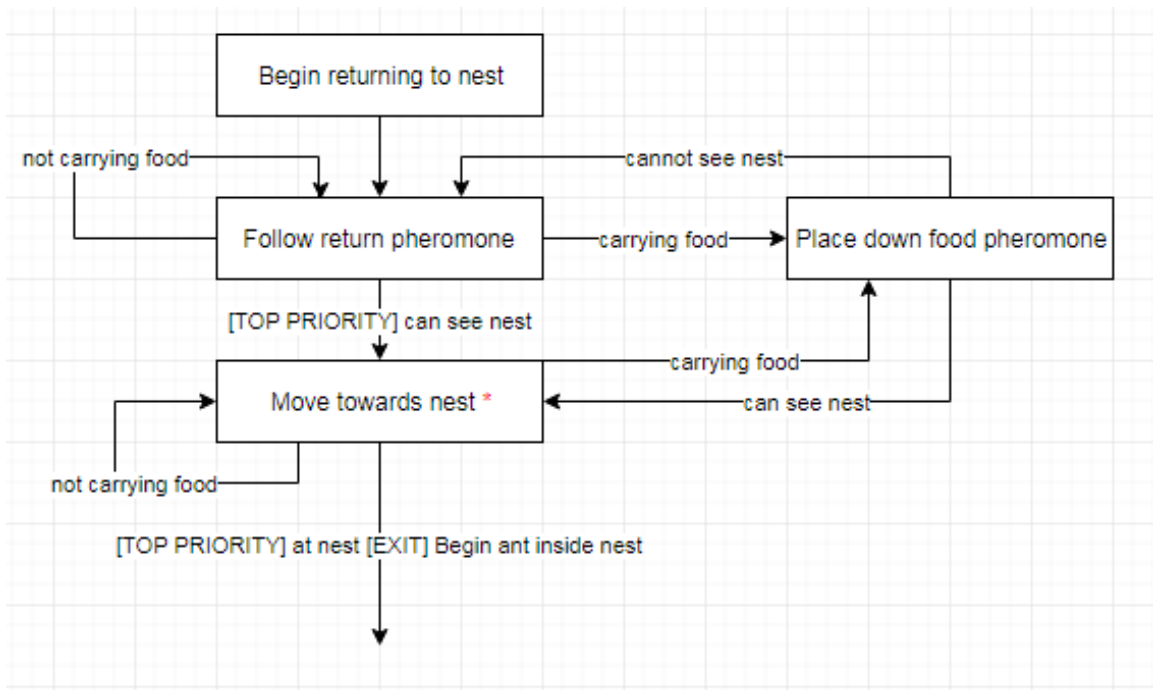


Figure 4: State Diagram for the Ant returning to the nest

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