Ant Colony Conundrum

New Mexico

Supercomputing Challenge

Team 118

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Executive Summary

Our project examines the effectiveness of decentralized systems, such as an ant colony, for solving a search problem. The problem that out project is attempting to solve is if a decentralized system such as an ant colony is capable of more effective search patterns than a centralized counterpart. In addition, we are looking at whether a system of numerous independent agents is able to adapt to environmental changes as a cohesive unit without specific communication between agents.

We will be examining the success of two primary behavior sets on a static and dynamic world and comparing the results. We will then attempt to create an ideal fusion of the two behaviors to maximize the efficiency of these ants. Finally, we will be exploring the usefulness of ant-based search patterns in real world applications such as search and rescue and hostile environments where robustness, reliability, and speed are key factors.

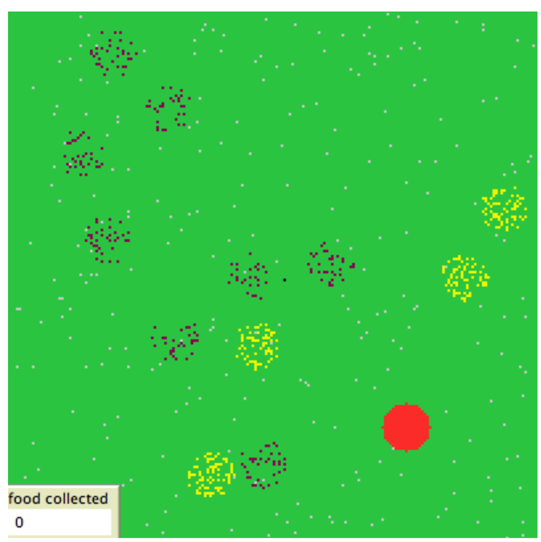
Colony Set up

The simulation was programmed with the intention of comparing two independent colonies side by side. The creation of the world is facilitated by a loop that duplicates a patch setup on the negative and positive sides of the X-axis. Every food pile is generated by a system that places food in a location within a radius measured to have a maximum food density of 256 seeds/pile.

```
if pile_true = 1 [
  set pile_count (pile_count + 1) ;increments pile counter
  ask patches [
    if (distancexy xm ym) <= pile_radius [ ;;creates a circle of food with area equivalent to 256 seeds
      if food_density <= 1 / (random 20 + .000001) [
        set pcolor yellow
        set mfood 1
        ask patch-at 200 0 [
          set pcolor yellow
          set mfood 1
        ]
      ]
    ]
  ]
]
```

The food is distributed into four possible densities. 100% density is red food. 25% density is represented by yellow food. 12.5% density represents purple food and randomly distributed food is shown in gray.

The exponential distribution is built to create equal food quantities of variable densities.

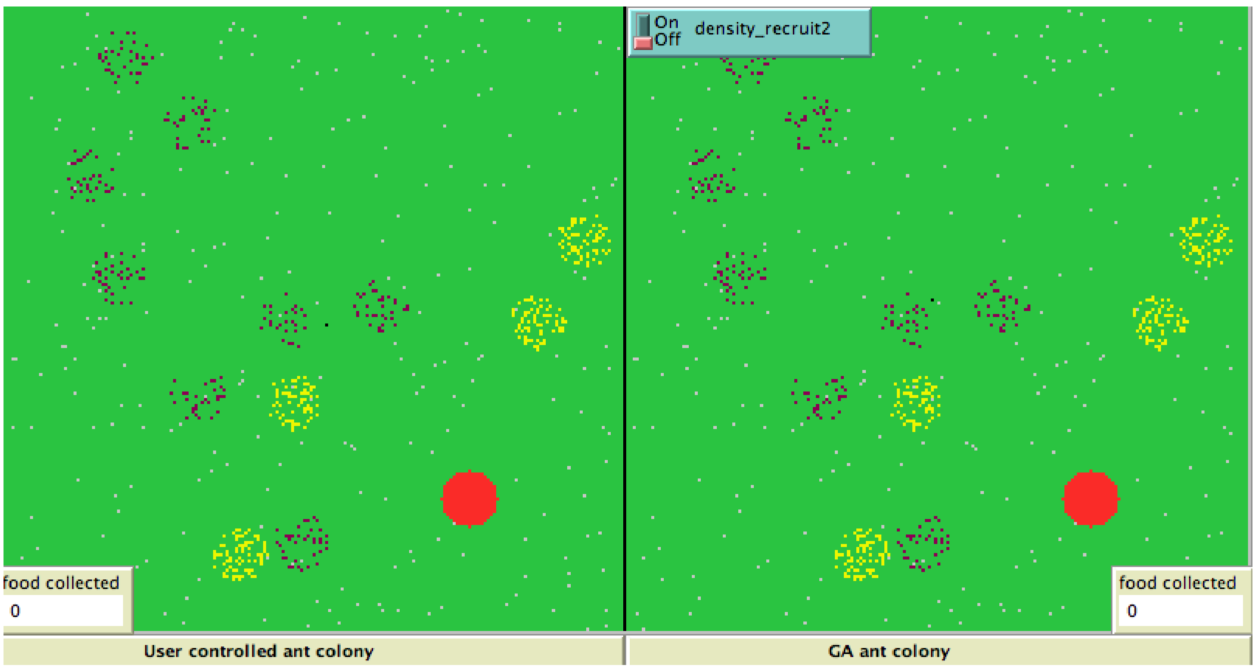


Red: 256 seeds * 1 pile = 256

Yellow: 64 seeds * 4 piles = 256

Purple: 32 seeds * 8 piles = 256

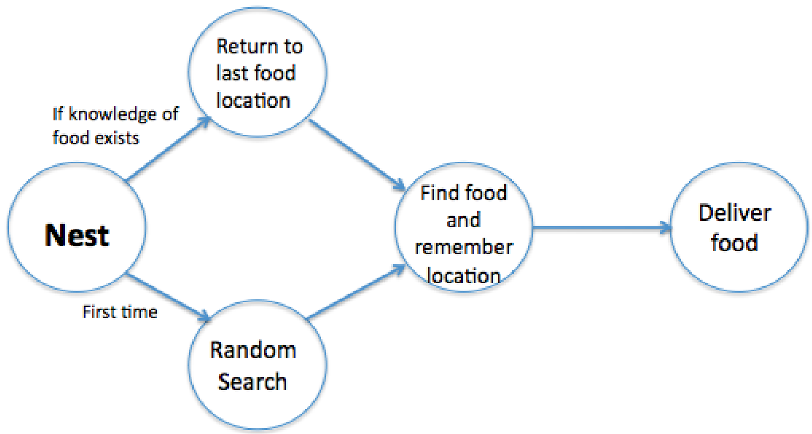
The simulation also creates two identical ant colonies, which it then compares in real time. These colonies are mirror images of each other with one difference: Their behavior parameters. For the purpose of accurate comparison, each colony is generated with identical food layout and colony size.



<u>Behaviors and Parameters</u>

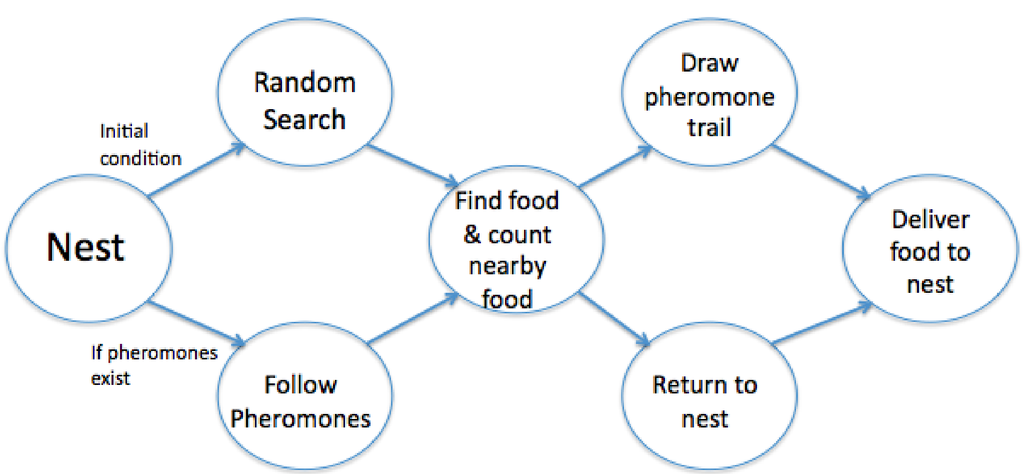
Each ant colony uses 2 major behavior sets: Site Fidelity and Density Recruitment.

Site Fidelity: Ants leave the nest using a random walk. They choose a random direction biased away from the nest to turn to and move forward a set amount. Upon finding food, they store the location internally. They then bring the food to the nest and return to the location of recently found food.



Density Recruitment: Ants leave the nest in a random direction and use the same random walk seen in Site Fidelity. Upon finding food, they make an assessment of food density in the neighboring area (food count **c**) (random 100/100 = P) (recruitment parameter = r).

P <= c + r . If this equation is true then ants will lay a trail. Ants at the nest will follow pheromones to a food source.



Pheromones

In nature, some ants have been proven to use a method of recruitment known as pheromones. Pheromones were discovered by placing absorbent paper between a nest and a food location. As the food source becomes more reliable, the strength of the chemical trail increases because more ants were returning to the location and laying trails. This effect is also seen in our simulation. The strength of the trails increases as the density of the food pile increases. These pheromone trails have also been proven to be volatile. All of the trails have an evaporation rate determined by a genetically optimized parameter.

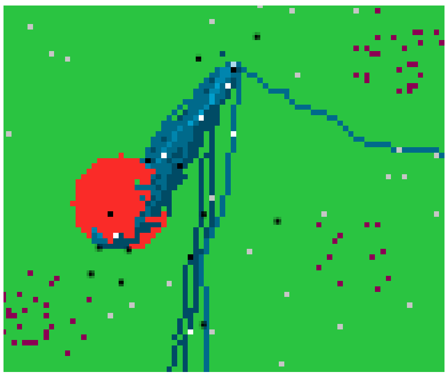
Trail evaporation equation

P = P initial * (1-E) if P initial > .001

P = 0 if P initial < .001

P = pheromone strength

E = evaporation constant (0<E<1)



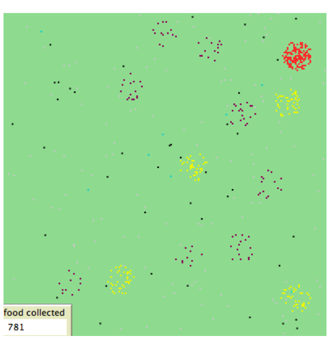
Dynamic Environment

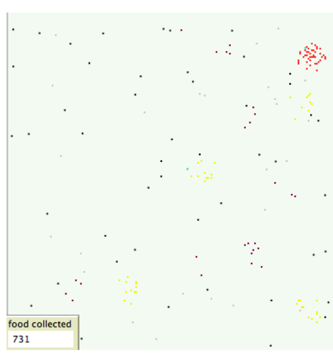
We are attempting to find a method of food collection that excels in both stationary and changing environments. For this reason, we programmed a simulation with a dynamic environment. This world begins with the same number of available food seen in the stationary model, but as time goes by, food amounts will decrease and increase with seasons.

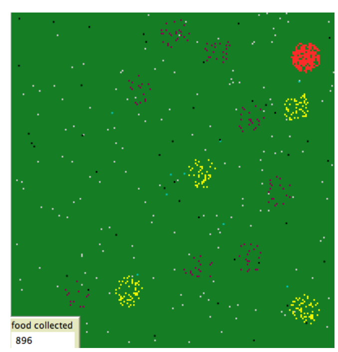
```
if (ticks / 6) = round (ticks / 6)[
  ask patches [
    if pcolor = red or pcolor = 123 or pcolor = 7 or pcolor = yellow [
      if random 250 = 1 [
        set pcolor background

      ]
```

This code block allows all the food to decrease at a rate of 0.067 % of the remaining total per tick over a 2500 tick interval. Resulting in approximately 50% fluctuation in food totals over all.

In addition to creating a fluctuation in available food, we created a visible environmental change in the way of seasons. The simulation will shift from dark green to white to a light green to symbolize a seasonal progression.



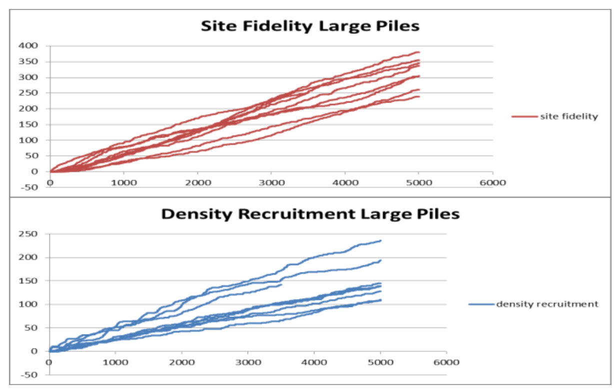




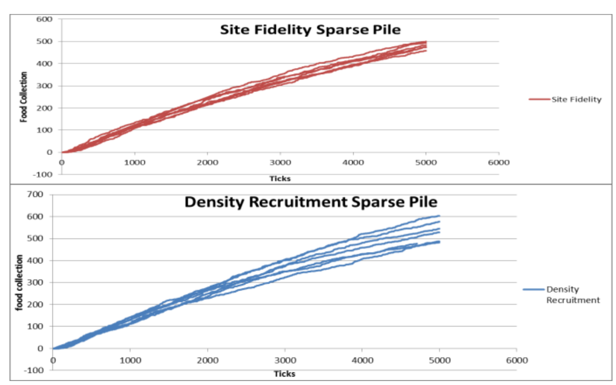
Graphs

To test the adaptability of different ant colonies, we tested many different scenarios of food distributions and trail evaporation. We tested our ant program several times to get the most dependable, reliable, and consistent data.

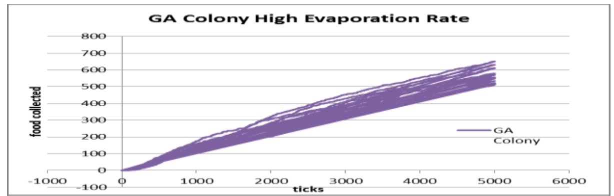
Random Food - Both graphs show the results of Site Fidelity and Density Recruitment over multiple trial runs. The food is distributed randomly. In this case, the ants perform almost the same not really varying much in behavior or food collection.

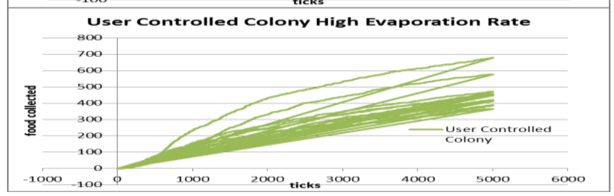


Large Piles/ Dense Food- The graphs are testing all dense piles of food. In this case Site Fidelity performs better than Density Recruitment. From collecting data and graphing we found that this was because in Density Recruitment, many of the ants never find food therefore they would never return to the nest, causing many of the ants never to pick up a pheromone trail.

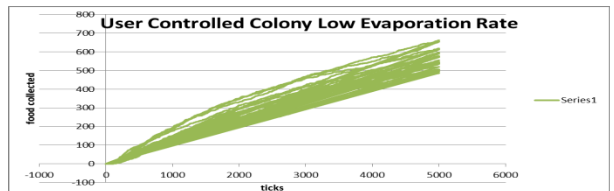


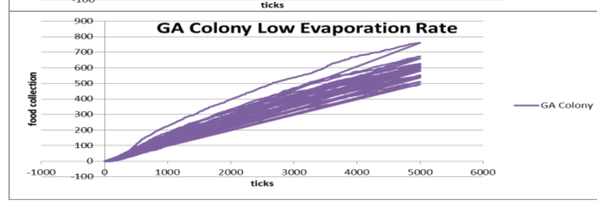
Sparse Piles- these graphs test sparse piles, which are the least dense pile of food in our program. Density recruitment performs better in this case. This is because Density Recruitment has a better chance of finding food and returning to the nest unlike the case with only a few dense food piles.





<u>High Evaporation Rate-</u> the higher the evaporation rate the faster the pheromone trails will disappear. The two colonies are in an environment with equal amounts of different piles of food. The GA colony performs better than the user-controlled colony with a high evaporation rate. It took the user controlled colony time to adapt to these extreme changes of their environment.





<u>Low Evaporation Rate-</u> In this case the ants had to adapt to the trails evaporation slower. The two colonies in this environment performed better than if the trails would evaporate faster and did not have to adapt to any sudden changes. Both ant colonies performed better as a result, with density recruitment depending on pheromone trails.

Conclusion

Ants are the world's greatest scavengers. Their behavior can teach us many things about how to find and collect resources through a distributed system such as a colony. However, few colonies live in an environment where their food availability is subject to extreme change. We are able to create these environments though the use of computer simulation. By running numerous tests, we have been able to pinpoint how to optimize the ant colonies in a system of extreme drought or extreme moisture. We have discovered how to optimize a colony for very dense and very sparse food sources, and we have learned how to adapt an ant colony to a changing environment through our knowledge of existing ant behavior and how parameters can affect it.

These new ant-based algorithms have numerous applications in the real world. A system of Ant-based robots would be extremely successful at both search-and-rescue style operations and in dangerous areas such as minefields. Because these ants are independent and highly efficient, a system of autonomous robots would be both cheap and reliable. The possibilities of robotic and digital ants are nearly endless.

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