# Ant Foraging Revisited

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## Abstract

Previous artificial (non-biological) ant foraging models have to date relied to some degree on *a priori* knowledge of the environment, in the form of explicit gradients generated by the nest, by hard-coding the nest location in an easily-discoverable place, or by imbuing the artificial ants with the knowledge of the nest direction. In contrast, the work presented solves ant foraging problems using two pheromones, one applied when searching for food and the other when returning food items to the nest. This replaces the need for using complicated devices to locate the nest source with simpler mechanisms based on pheromone information, which in turn reduces the ant system complexity. The resulting algorithm is orthogonal and simple, yet ants are able to establish increasingly efficient trails from the nest to the food in the presence of obstacles.

Depending on whether they are carrying food or not, ants are sensitive to and deposit specific pheromones. When foraging, ants move stochastically in the direction of increasing food pheromone, and deposit some amount of nest pheromone. If there is already more nest pheromone than the desired level, the ant deposits nothing. Otherwise, the ant "tops off" the pheromone value to the desired level. As the ant wanders away from the nest, its desired level of nest pheromone drops. This decrease in deposited pheromone establishes an effective gradient. When the ant is carrying food, the movement and pheromone laying behaviors use the opposite pheromones than when exploring for food.

The basic algorithm is made stochastic in two ways. First, our model assumes that no more than ten ants may occupy a grid square; an ant will move to its best choice among non-full, non-obstacle locations. Second, we add some degree of randomness to the ant's choice of location. Ants move in random order. Ants live for 500 time steps; a new ant is born at the nest each time step unless the total number of ants is at its limit. Pheromones both evaporate and diffuse in the environment.

Our experimental substrate was a 100x100 non-toroidal grid environment, with a nest located at (70,70) and food at (20,20), and with 1000 ants. The experiments were run on the MASON simulation library, presented in an accompanying paper at this workshop. In the experiments, different approaches were compared by the total amount of food brought back to the nest. For each approach, we drew a sample of 50 runs, and applied a Welch two-sample statistical test at 95% confidence. Separate experiments investigated foraging in the presence of obstacles; for this paper we did not use any such obstacle in the environments.

We first compared pheromone-depositing rules. The rule common in the literature is to simply add to the environment a desired — usually fixed and small — amount of pheromones. We compared this rule to our "topping off" rule described earlier. In this experiment, our "topping off" rule was statistically significantly superior to the common rule, returning well over twice the total amount of food.

We then tested system performance under different evaporation rates and different diffusion rates. Moderate diffusion rates significantly outperformed lower and higher amounts. Similarly, small evaporation rates performed best, but not statistically better than no evaporation at all. Large evaporation performed poorly.

We also compared different rates of exploration versus exploitation, by varying the degree of stochasticity in the movement rules. We imagined that a moderate degree of exploration would permit a good balance between finding shorter paths and retrieving many food items. However, experiments showed that the greedier the behavior, the significantly higher the total amount of food foraged. Further analysis revealed that, due to a constraint on maximum number of ants per location, the algorithm was already performing a form of hill-climbing for shorter trails. Ants "bumped" to less desirable locations would eventually smooth out the path until it became optimal. In our final experiment, we laid down a clearly suboptimal trail of pheromones for ants to follow, and observed that the trail was successfully smoothed to the optimal one.