

## Effectiveness of Emerged Pheromone Communication in an Ant Foraging Model

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### Abstract

The collective behavior of social insects has been a puzzling problem for scientists for a long time. In particular, it is well known that ants solve difficult problems, for instance selecting the shortest pathway by communicating with each other via pheromone. How is it possible for such simple creatures to coordinate their behaviors and to solve problems as a whole? This paper focuses on the emergence of the pheromone communication system based on an ant foraging model in which neural networks of ant agents evolve according to the result of foraging. The computer experiments show that the ant agents using emerged communication with one type of pheromone are more adaptive than the ant agents not using pheromone communication or the ant agents using human-designed communication with 2 types of pheromone. This paper also discusses the reason for this superiority of the evolved pheromone communication.

**Key words:** ant colony, pheromone communication, swarm intelligence, artificial life.

### 1 Introduction

Complex and adaptive behavior of population emerges in social insects like ants and bees, though individuals seem to follow a relatively simple set of rules. The last decade has seen an explosion of research in fields variously referred to as swarm intelligence or collective intelligence. Especially in ants, pheromone communication is the key to understanding their swarm intelligence. The fundamental question regarding pheromone communication is: How have the pheromone communication systems emerged? This topic is not only a biological one, but, at the same time, a cross-disciplinary one [1, 2, 3, 4].

As a first step towards the origin of pheromone communication, we focus on the adaptive property of pheromone communication in population of agents, depending on the kind of pheromone communication. There can be two computational approaches to this issue, one is to define, a priori, both the meaning of pheromone and the rules of behavior for agents, and the other is to let them establish communication autonomously through learning or evolution. The latter is effective especially when the specific knowledge for solving the problems is limited or unknown. However, it is quite difficult to establish communication without a priori knowledge because pheromone communication

doesn't function at all until the following two rules autonomously emerge in accordance with each other: "In what kind of situation should the agents secrete some kind of pheromone?" and "How should they act when they detect some kind of pheromone?"

To pursue this issue, some models have been proposed, including the pioneering model by Collins and Jefferson in which the mechanism for the evolution of pheromone communication was implemented [5] and a simple model by Kawamura and Ohuchi in which pheromone communication emerged in the environment where two colonies of artificial ants competed for food resources [6]. Based on these studies, we developed an ant foraging model, in which there can be several kinds of pheromone [7]. This paper reports our current state of the research based on the computer experiments using a simple model for evolution of pheromone communication, in which neural networks of ant agents evolve based on the result of foraging.

### 2 The ant foraging model

This section offers the brief summary of our ant foraging model which was proposed in our previous paper [7]. The model is based on multi-agent modeling and is inspired by foraging ants in nature. Foraging ant agents move around the  $X \times Y$  grid environment in which there are food resources, pheromone and a nest. Each colony consists of  $N_a$  ant agents and their objective is to look for and carry to their nest as many food resources as possible.

Ant agents could secrete several types of pheromone in the same environment. The type of pheromone is identified by the subscript  $v$  ( $v = 1, 2, \dots$ ). They have no effect on each other. Each ant agent can drop pheromone on the ground by dropping action. Dropped pheromone gradually evaporates and diffuses in the air. Ant agents can detect diffusing pheromone only. Dropped pheromone and diffusing pheromone at position  $(x, y)$  are represented by  $T_v(x, y)$  and  $P_v(x, y)$  respectively. Then the diffusion process is defined by the partial differential equation as follows.

$$T_v^*(x, y) = (1 - \gamma_{eva})T_v(x, y) + \sum_{k=1}^{N_a} \Delta T_v^k(x, y) \quad (1)$$
$$\Delta T_v^k(x, y) = \begin{cases} Q_p & \text{if } k\text{-th ant agent on the grid} \\ & \text{put the pheromone } v \quad (2) \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned}
 P_v^*(x, y) &= P_v(x, y) + \gamma_{dif}(P_v(x - 1, y) \\
 &+ P_v(x, y + 1) + P_v(x, y - 1) + P_v(x + 1, y) \\
 &- 5P_v(x, y)) + \gamma_{eva}T_v(x, y)
 \end{aligned}
 \tag{3}$$

where the parameters  $\gamma_{eva}$  and  $\gamma_{dif}$  are the evaporation rate and diffusion rate of pheromone per a time respectively. Also, the letter “\*” in superscript means that this represents intensity of pheromone at time  $t + 1$ , and  $Q_p$  is the intensity of pheromone dropped by an ant agent.

All ant agents in each colony are homogenous, and have the same mechanism for action decision. Each agent performs actions in the following order. 1) The ant agent senses whether a food resource exists on the grid, senses whether the grid is a part of nest, and recognizes whether it is carrying a food resource. 2) The ant agent might drop a certain type of pheromone depending on the output of the neural network. Each ant agent can use  $V$  types of pheromone. In case  $V = 2$ , ant agents can use pheromone  $v = 1$  and pheromone  $v = 2$  in the experiment. 3) When there is a food resource, if the ant agent carries no food, it picks it up, and if the ant agent has a food resource and is on the nest, the ant agent drops it. 4) If the ant agent did not perform the previous action, it selects and perform one action from 5 options according to the output of the neural network: “wait (do nothing)”, “move forward”, “turn backward”, “turn left”, “turn right”. If the ant agent selects an action that is impossible to do, it waits instead.

All ant agents have the same simple two-layer neural network with  $3 + 4V$  sensory input and  $5 + 2V$  output neurons. Action selection is stochastically decided according to the probability from output value of a neural network.

The output value  $I_i$  ( $i = 1, \dots, 3 + 4V$ ) of  $i$ -th sensory input neuron of an ant agent is defined as follows.

$$I_1 = \begin{cases} 1 & \text{if food is present} \\ 0 & \text{otherwise} \end{cases}
 \tag{4}$$

$$I_2 = \begin{cases} 1 & \text{if the ant agent is on the nest} \\ 0 & \text{otherwise} \end{cases}
 \tag{5}$$

$$I_3 = \begin{cases} 1 & \text{if the ant agent has food} \\ 0 & \text{otherwise} \end{cases}
 \tag{6}$$

$$I_{4+4(v-1)\sim 7+4(v-1)} = \begin{cases} 1 & \text{if the } P_v^s \text{ is satisfied} \\ 0 & \text{otherwise} \end{cases}
 \tag{7}$$

Here, the position of an ant agent is assumed to  $(x, y)$ , and its neighbor position is  $(x', y') \in \{(x - 1, y), (x + 1, y), (x, y - 1), (x, y + 1)\}$ .  $P_v^s(x', y')$  is the probability to fire input neuron of pheromone sensory input neurons. This stochastic firing function is used when obtaining the discrete values of  $I_{4+4(v-1)\sim 7+4(v-1)}$ , which depends on the gradient of density of pheromone and is defined as follows.

$$P_v^s(x', y') = \frac{1}{1 + \exp\left(-\frac{P_v(x', y') - P_v^{\#}(x, y)}{T}\right)}
 \tag{8}$$

where the function  $P_v^{\#}$  indicates the average intensity among neighbor grids.

The output value  $O_j$  ( $j = 1, \dots, 5 + 2V$ ) of  $j$ -th output neuron is calculated by using following regular equations.

$$O_j = f\left(\sum_{i=1}^{3+4V} w_{ij}I_i - \theta_j\right)
 \tag{9}$$

$$f(x) = 1 / (1 + \exp(-x))
 \tag{10}$$

where  $w_{ij}$  and  $\theta_j$  are the weight and the threshold of the neural network. The values of 5 outputs ( $O_{1\sim 5}$ ) correspond to “wait”, “move forward”, “turn backward”, “turn left” and “turn right” actions respectively and the value of  $2V$  outputs ( $O_{6+2(v-1)}$  and  $O_{6+2(v-1)+1}$ ) correspond to “dropping pheromone  $v$ ” and “doing nothing about pheromone  $v$ ” actions.

The genetic algorithm (GA) is adopted to evolve the neural networks of ant agents. A set of weights and thresholds describing a neural network is directly encoded to each genotype. The population size is  $N$  and all genotypes are initialized to random values of  $[-0.5, 0.5]$ . A fitness function is defined to be 1 plus the number of food resources that have been stored in the nest. New generation with  $N$  individuals is generated by the roulette wheel selection and mutation. The mutation operator is defined as adding a random real number of  $[-0.5, 0.5]$  to the value in each locus with the mutation probability  $P_m$ . These processes are repeated until the final generation  $g_{max}$ .

### 3 Computer experiments

The parameters of ant foraging and GA were set as  $(X, Y, N_a, t_{max}, Q_p, \gamma_{eva}, \gamma_{dif}, T) = (50, 50, 40, 1000, 1, 0.1, 0.1, 0.002)$  and  $(N, g_{max}, P_m) = (20, 2000, 0.05)$ . The size of the nest was  $5 \times 5$  and it was located in the center of the environment. 72 food resources were put on a randomly selected  $3 \times 3$  area at the time  $t = 0$ . Each grid in the area had 8 food resources. Under these conditions, several trials were conducted for each  $V$  ( $V = 0, 1, 2$ ).

Fig. 1 shows the moving average of food resources stored in the nest. It increased sharply to the range between 7 and 10 by 3000 generations in all graphs, and from then on, transitions differed depending on the parameter  $V$ . In the case of  $V = 0$ , most trials showed that each moving average remained at around 7. In the case of  $V \geq 1$ , transitions were classified into two typical classes, and thus, it would be supposed that there are at least two evolutionary pathways. One was the case that moving average remained between 7 and 10, which is similar to the case of  $V = 0$ . The cases 1a and 2a correspond to this class. The other was the case that moving average increased beyond 10. The cases 1b and 2b correspond to the class. The moving average had a tendency of swinging between 15 and 25 in 1b and it gradually increased beyond 7 in 2b. We see that the case 1b outperformed the other cases.

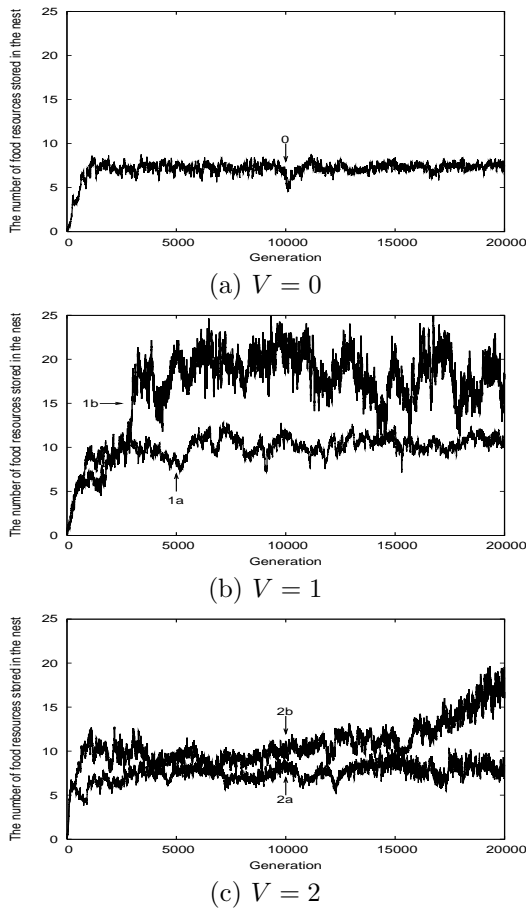


Figure 1: Moving average of the number of stored food resources.

It was found from the analysis of neural network that the ant agents in case 1b behaves as follows. Overall, the ant agents move forward with probability of about 90% and it turns right with probability of about 10%. However, the ant agents turns right with probability of about 40% only in cases in which they exist on the falling gradient of pheromone. Therefore, we can assume that the pheromone moderately indicates the presence of both food and a nest. The ant agents without food hardly secrete pheromone. The ant agents with food secrete pheromone with the probability of 40% and they on the nest secrete pheromone by the probability of 20% even if they aren't carrying food. Therefore, the pheromone moderately indicates the presence of both food and a nest.

We conducted additional experiments on the ant agents with human-designed pheromone communication (Fig. 2) in order to evaluate the effectiveness of emerged pheromone communication. The ant agents used two types of pheromone (food pheromone and nest pheromone) and were expected to do shuttling behavior between the nest and the food locations efficiently by using them. In the experiments, human-designed ant agents and the evolved ant agents (in the 20000th generation in all cases shown in Fig. 1) performed the foraging task 1000 times each. It is clearly shown from Table 1 that evolved

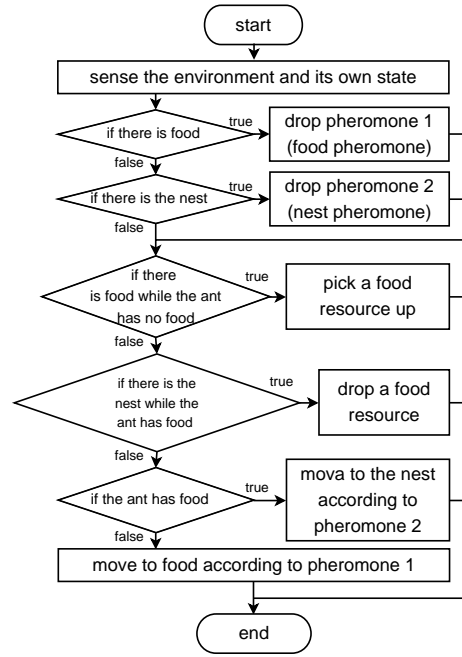


Figure 2: Behavior of human-designed ant agents.

Table 1: Average number of stored food resources.

Ant agent	Average
0 ( $V = 0$ )	8.8
1a ( $V = 1$ )	18.9
1b ( $V = 1$ )	28.0
2a ( $V = 2$ )	14.4
2b ( $V = 2$ )	24.7
human-designed	12.4

pheromone communication outperformed the human designed pheromone communication, in other words, some clever pheromone communication beyond human design emerged through evolution.

#### 4 Superiority of emerged pheromone communication

The results of the first experiments are summarized as follows. The ant agents using pheromone ( $V \geq 1$ ) could be clearly more adaptive than the ant agents without pheromone ( $V = 0$ ). In other words, emergent pheromone communication could be adaptive. However, the results also show that it is not necessarily true that the more the number of available pheromone type increases, the more the ant agents could be adaptive. This might be because of the difficulty in establishing the meaning of pheromone or communication protocol based on multiple types of pheromone. We believe that more sophisticated and powerful mechanisms of learning or evolution could make pheromone communication work better.

The results of the second experiments show that emerged pheromone communication outperformed

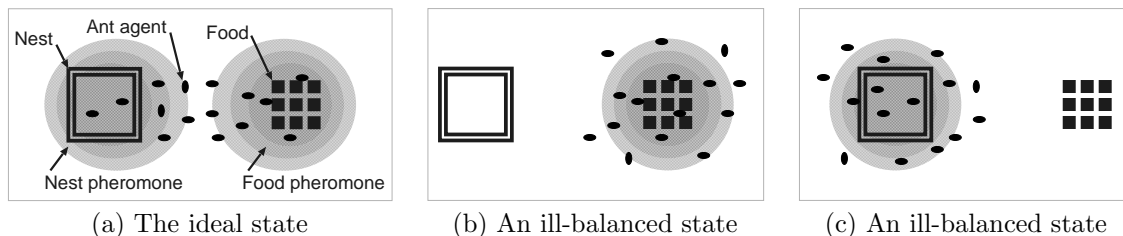


Figure 3: The ideal and the ill-balanced states in the case of 2 types of pheromone.

human-designed pheromone communication. Why did emerged pheromone communication outperform human-designed one? To answer why emerged pheromone communication performed better, we observed the behavior of ant swarms and the spatial distribution of pheromone across the environment.

In the case of human-designed ant agents, it seems an ideal state that equal amount of two types of pheromone exist in the environment (Fig. 3 (a)). However, we found that ill-balanced states (Fig. 3 (b) and (c)) frequently happened, which mean inefficient concentration of the ant agents around the food or the nest. This unexpected result shows the difficulty in controlling the behavior of ant agents by using pheromone communication, which was caused by its emergent property.

In contrast, ant agents hardly crowded the food or the nest in case 1b. The results shown in previous section suggests that the ant agents in case 1b behaved as follows. Ant agents secrete one type of pheromone with high probability both when they are in the nest and when they have food. So, in this case, the pheromone moderately indicates the presence of both food and the nest in the emerged pheromone communication. Ant agents have evolved to have a tendency to move to the places with more intensive pheromone. Therefore, ant agents move around the peripheries of both food and the nest. These ant agents don't behave optimally, because it has no way of distinguishing food and nest by using only one type of pheromone. However, it is a significant fact that we hardly observe the ill-balanced states which appeared frequently in the case of human-designed ant agents.

Above discussion is summarized as follows. While the uniquely existing type of pheromone acquired a moderate meaning of the presence of both food and the nest through evolution, the diversity of pheromone distribution and the diversity of the ant agents' collective behavior got to be maintained at proper levels, which realized the robust foraging behavior of ant agents.

## 5 Conclusion

This paper describes the ant foraging model for the evolution of pheromone communication and discusses the result of the computer experiments. The computer experiments show that the ant agents using emerged communication with one type of pheromone are more adaptive than the ant agents not using

pheromone communication or the ant agents using human-designed communication with 2 types of pheromone. The reason for the superiority of the evolved pheromone communication is the diversity of pheromone distribution and the diversity of the ant agents' collective behavior got to be maintained at proper levels, which realized the robust foraging behavior of ant agents.

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