2013 International Conference on Computational and Information Sciences

A Model of Rescue Task in Swarm Robots System

Bailong Liu, Pengpeng Chen, Guanjun Wang
College of Computer Science and Technology
China University of Mining and Technology
Xuzhou, China
liubailong@cumt.edu.cn

***Abstract*—Swarm Intelligence inspired by social animals has gained a lot of attention recently. It always appeals to the collective behaviors observed in social animals. In this paper, a mean field model of rescue process in robotic system is given and its dynamic with noise and emergency ability is implemented by Monte Carlo type of simulation.**

Keywords- Swarm Intelligence; mean field model; Monte Carlo

I. INTRODUCTION

Swarm Intelligence(SI) which is inspired by social animals has gained a lot of attention in the field of control and Artificial Intelligence. In social animals complex collective behaviors emerge from the interactions of individuals which perform simple behaviors. This is achieved through self-organization, in which order at the global level of a system emerges from the interactions between the lower level components of the system. In the theoretical point of views, the self-organization implies balances between positive feedback and negative feedback.

Foraging behavior in ant colonies have come to be viewed as a prototypical example of how complex group behavior can arise from simple individuals[1].

The cooperation in robotic systems can appeal to the self-organization phenomenon of SI. In the rescue task of a ruin field, the robot needs to transport the pieces of ruins to free space. The process is similar to the foraging behavior of the ant colonies. Each ruin piles can be seen as the sources in the foraging process, whose size implies the emergency of been collected. Also this can be sensed by the robots. The more emergent the sub-task is, the more robots are needed. In order to make other robots have the information of the sub-task, the interactions between the robots are needed. So a pheromone is used to indicate how many robots engage in this sub-task. This can be implemented by material like "disappearing ink" in [4] or by blackboard communication. The aim of the task is to clear the piles by assigning robots reasonably. We assume that the distances of the free space to the piles are equal.

This paper is organized as follows: the related works on swarm foraging behavior about the self-organization are summarized next. And then the model of rescue process based on mass recruitment is built and analyzed. Finally, the simulation and analyses based on the model is implemented by Monte Carlo method.

II. RELATED WORKS ON SWARM FORAGING

In order to understand the self-organization in SI system, it is necessary to observe the behaviors of social insects. And in this complex behaviors, the foraging behavior in ant colonies is the typical example[1]. Also in real word, foraging behavior is the reduction of mining, garbage collecting, explosive cleaning, rescuing and other tasks in dangerous environment. So, researching on the foraging behavior can give some inspiration in these tasks.

There are many foraging strategies in each ant family. And the combination of these strategies makes the system exhibit the feature of self-organization: emergent patterns, multistabiltiy, and bifurcation [2]. Holldobler[3,4] divides the various types of foraging recruitment into four groups: (1) Tandem Running; (2) Group Recruitment; (3) Trail-based Group Recruitment; (4) Mass Recruitment. The fourth one is one of the most complex forms of social behaviors in ant colony. In this paper the case of mass recruitment is considered. In the process of foraging, the scout robot returns to the nest and lays a pheromone trail after it discovered a food source. Then the foragers will be activated by the trial and become recruits. These recruits can become recruiters in their turn.

Inspired by the ant foraging behavior, most researchers of Intelligence applied the mechanisms observed in ant foraging behavior to different areas, such as optimization algorithms, robotics. M.Dorigo developed the ant colony algorithm. It is then well used in Travel Salesman Problems, Assignment Problems, Job-shop and other optimal problems[1]. The simple interactions observed in foraging behavior of ants also inspired many robotic researchers to coordinate the robots. This gives the robotics system higher reliability, adaptability and flexibility. Romas et al. took advantage of the cognitive maps introduced in [5], and endowed the life cycle to foragers. Through evolving, they can adapt the dynamic environment well. Tsankova and Georgieva[6] simulated a two-robot foraging behavior using artificial pheromone. They concluded that the performance increased as the number of the robot increased. Sugawara[7] defined some basic behavior of robots, and gave the relation between the number of the robot and the completion time of the foraging task in both physical experiments and simulations. Chen Weidong[8] proposed a queue coordination method based on in foraging tasks of multiple robot system. From the experiments, it is proved that this method can reduce the number of conflict and improve the performance.

978-0-7695-5004-6/13 $26.00 © 2013 IEEE
DOI 10.1109/ICCIS.2013.343

By far, the most rigorous theoretical representation of a recruitment system based on differential equations is developed by Nicolis and Deneubourg[2,3]. They account for the competition between trails in the presence of an arbitrary number of sources. Their model makes a macroscopic approach to the mass recruitment phenomenon in ant system, and uses pheromone concentration as the principal variable. It is mainly devoted to the choice of orientation among more than one trail upon leaving the nest. But their model in the precondition of the food will never decrease. In the present paper, the model extends their model and considers the trail distance and the food consumption. Nicolis and Deneubourg make important initial assumptions regarding the recruitment system, as listed below: (1) Pheromone trails are always followed error-free from nest to food source. (2) Ants are either within the nest or following a trail and wandering does not occur. (3) Direct interactions between individuals are ignored; only through pheromone is possible. (4) The outgoing flux of ants from the nest is a constant. These link the rules of individual to the mathematical descriptions. In this paper, the foraging model is extended and analyzed through simulation, and then an improved foraging strategy of swarm robots is proposed. The experiments show that the improved method can increase the performance and reduce the conflicts between robots.

III. THE MODEL OF RESCUE PROCESS

The macroscopical result of the system is described by the dynamics of the states i.e. the pheromone concentration and the size of ruin pile. So we use differential equations describe the time evolution of the concentration of pheromone c_i to pile i and the size e_i of pile i. The change of c_i is determined by two aspects: the production by laying, $\phi q_i P_i$ and the disappearance by evaporation, $-vc_i$, which makes the robots not conduct one sub-task only. ϕ represents the number of robots from the free space. q_i represents the quantity of pheromone laid to pile i. So it is related to the size of the pile i. And the evaporation rate of the pheromone is v. Each robot in the free space has to select one according to the relative attractiveness of the pile i, P_i. The formula of P_i is

$$P_i = \frac{(k_i + c_i)^l}{\sum_{j=1}^{s}(k_j + c_j)^l}. \quad (1)$$

k_i is the response threshold of a pile, this means the emergency level of the rescue sub-task. l stands for the sensitivity to a pile on the concentration of pheromone c_i presents. Here it will be fixed to a value $l = 2$ and $k_i = 1$. s is the number of piles.

As mentioned above, q_i depends on the size of the pile i. So we define the size of pile i, $e_i \geq 0$. Each time ϕ robots flow out of the free space and P_i of them move to the pile i. So the size of pile i decreases at the speed of ϕP_i. We obtain

$$\frac{de_i}{dt} = -\phi P_i = -\phi \frac{(1+c_i)^2}{\sum_{j=1}^{s}(1+c_j)^2} \qquad i = 1,2,..,s \quad (2)$$

Because q_i is an increasing function of e_i. So we define $q_i = \eta e_i$ for simplicity and assume η is constant for the same swarm. From the analyses mentioned above, we obtain

$$\frac{dc_i}{dt} = \phi\eta e_i \cdot \frac{(1+c_i)^2}{\sum_{j=1}^{s}(1+c_j)^2} - vc_i \qquad i = 1,2,...,s \quad (3)$$

In this model, we have four types of feedback:

(1) a positive, nonlinear feedback of pheromone concentration c_i through the function P_i;

(2) a negative, linear feedback of c_i through evaporation;

(3) a negative nonlinear feedback of pile $j \neq i$ on pile i associated with competition;

(4) a negative nonlinear feedback of e_i decrease through the function P_i. The system behavior is a combination of these feedbacks.

Here are two conditions of the system:

$$e_i \geq 0 \qquad c_i \geq 0. \quad (5)$$

We can see from the system that its stationary solution occurs in

$$\frac{de_i}{dt} = 0 \text{ and } \frac{dc_i}{dt} = 0. \quad (6)$$

Because e_i will decrease until it comes to zero. Substitute it into equation (3), we can obtain $c_i = 0$. When the pile i is cleared($e_i = 0$), the pheromone concentration of pile i will decrease linearly.

The dynamics of the solution is calculated in the ideal situation, in which the decision of selecting a trail is determined. This is not suitable to the situation in real world. To solve this problem, one method is to augment (1) or (4) by noise term. This leads to a Fokker-Planck equation for the probability density of occupying various trails. The other method is to implement it through a Monte Carlo type of simulation. Here we appeal to the Monte Carlo simulation.

IV. MONTE CARLO SIMULATIONS

The advantage of Monte Carlo type of approach is that one can simulate the process of interest rather than solve master equations modeling it at a probabilistic level[4].In the simulation the stochastic aspect of the process is also considered. There are some variables in the simulation: the number of robots, the concentration of pheromone in each trail, the size of each pile, and the evaporation rate of pheromone. We give the settings and processing steps as follows.

- Initial conditions: The pheromone concentrations and numbers of robots over each pile are fixed to zero. The initial emergency of each pile is different. The initial size of each piles is $e_1 = 10, e_2 = 5, e_3 = 8$. According to ϕ which is normalized before the simulations, one robot comes out of the free space in each simulation step. And we also computer the time cost a forager to a pile, which is much longer than a simulation step (10 times). In addition, $\eta = 0.1$ and there are three piles needed to be cleared.
- Decision process: When a robot arrives at the free space, it should decide which pile to be selected. Initially the piles will be selected at the same possibility. As soon as one robot selected a pile, the probability will differentiate. The choice of each pile is determined by (1). Here we generate a random number from uniform distribution. Compared with each P_i, if it is less than P_1, the robot will select pile 1. If it is between P_1 and $P_1 + P_2$, it will select pile 2, and so on.
- Time evolution: The pheromone concentration in each trail will gradually disappears through the parameter ν. So we update the possibilities showed in equation (3) at each simulation step.

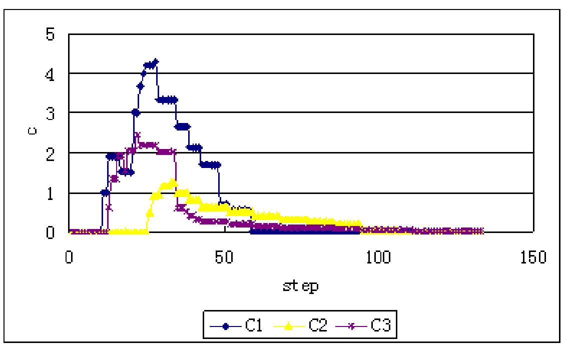

Figure 1. Time evolution of pheromone concentration

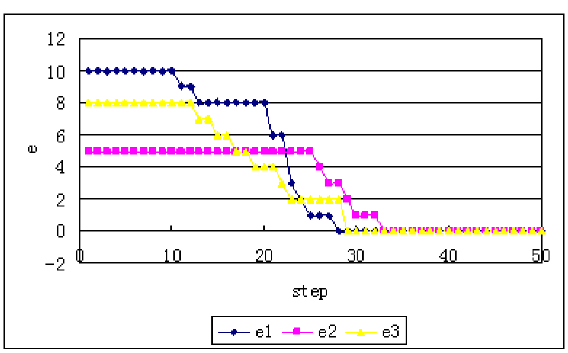

Figure 2. Time evolution of the size of each pile

The simulation is implemented for 50 times. Fig.1 and Fig. 2 show the time evolution of pheromone concentration and the size of each pile respectively. In 82% of simulations the biggest pile is worked on firstly. The other situations may be caused by the stochastic element in selecting. This exhibits the diversity of the system. In Fig. 2, we can see that the sizes of the piles are always approximate in one phrase because the system expected the balance the requirement of different sub-tasks. When the sub-task is found relative emergency, more robots will engage in it. So the pheromone concentration increases. This exhibits the adaptation of the swarm-based system. When a pile is cleared, the pheromone concentration to the pile decreases linearly which satisfies the theoretical model. But there is still a time delay for the robot to recognize it immediately. This is mainly caused by the pheromone evaporation.

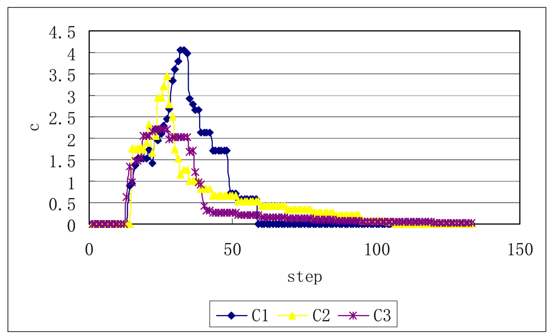

Figure 3. Time evolution of pheromone concentration in dynamic situation

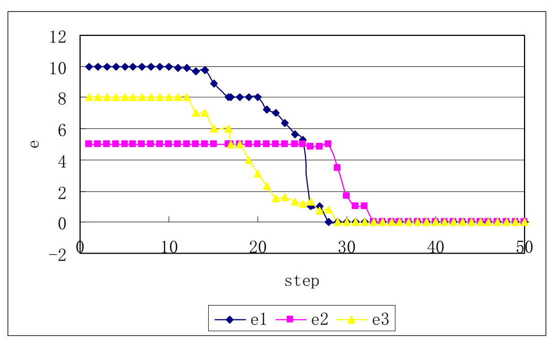

Figure 4. Time evolution of the size of each pile in dynamic situation

In order to prove the adaptability of our model, the emergency level of rescue sub-task 2(namely k_2) is changed. When the time step is before10, $k_2 = 1$. And after that time $k_2 = 2$. At last $k_2 = 1$ when time step is 20. This means, the emergency level of rescue sub-task 2 has a higher value in the rescue process. From the time evolution of pheromone concentration and the size of each pile respectively show Fig.1 and Fig. 2 , we can see that, our model has a nice adaptability. Because the value of pheromone concentration has a high jump after time step 10, and then the size of the ruin pile in sub-task 2decreases faster than that of sub-task 1 which should be dealt with first. Also after time step 20, the decreasing speed of pile 2 is slower, because sub-task1 has more piles needed to be moved relatively.

V. CONCLUSIONS

In this paper, we appeal to the foraging behavior in ant colonies and give the model of the rescue task in robot swarms by mean field method. The dynamic of the system with noise is implemented by Monte Carlo type of simulation. From the simulation, robots can clear the piles as we expected, and it also has a nice adaptability when the situation is changed. It is concluded that the robots have no immediate information about the tasks. This can be solved by some direct communication or giving individual the reasoning capability which will be researched in future.

ACKNOWLEDGMENT

This paper is supported by National Natural Science Foundation (NSFC 61202478).

REFERENCES

[1] Bonabeau E, Dorigo M, Theraulaz G, "Swarm intelligence: From natural to artificial systems," first ed., New York Oxford, Oxford University Press, 1999.

[2] Nicolis, S.C., Deneubourg, J.L., "Emerging patterns and food recruitment in ants: an analytical study," Journal of Theoretical Biolog. No,198, pp.575-592, 1999

[3] Nicolis S.C. DETRAIN C., DEMOLIN D., Deneubourg J.L., "Optimality of Collective Choices: A Stochastic Approach," Bulletin of Mathematical Biology. Vol.65, pp. 795-808, 2003.

[4] Mark Russell Edelen, "Swarm Intelligence and Stigmergy: Robotic Implementation of Foraging Behavior," Graduate School of the University of Maryland, 2003.

[5] Pratt, S. C.,"Recruiment and other communication behavior in the Ponerine ant Ectatomma ruidum," Ethology. Vol.81, pp.313-331,1989

[6] Holldobler, B. and Wilson, E. O., "The Ants," Cambridge, Mass.: Harvard University Press, 1990.

[7] Ramos V., Ferandes C., Rosa A.. Social Cognitive Maps, "Swarm Collective Perception and Distributed Search on Dynamic Landscapes," Brains, Minds and Media-Journal of New Media in Neural an Cognitive Science,2005.

[8] Tsankova D. D., Georgieva V. S., "From Local Actions to Global Tasks: Simulation of Stigmergy Based Foraging Behavior," IEEE International Conference on Intelligence Systems, 2004, pp.53-358.

[9] Sugawara K., Watanabe T., "A Study on Foraging Behavior of Simple Multi-robot System," IEEE 2002 28th Annual Conference of the Industrial Electronics Society(IECON 02), 2002, pp. 3085-3090.

[10] Wang Shen, Chen Wei-Dong, "Queue coordination strategy based on local sensing in distributed multiple mobile robot systems," ROBOT, vol.24, pp.540-544,2002.

[11] Wei-Min Shen, Cheng-Ming Chuong, Peter Will, "Simulating Self-Organization for Multi-Robot Systems," International Conference on Intelligent and Robotic Systems, Switzerland, 2002, pp. 2776-2781.