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Adaptive Control in Swarm Robotic Systems

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ADAPTIVE CONTROL IN SWARM ROBOTIC SYSTEMS

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Abstract. Inspired by the collective behavior observed in natural insects, swarm robotics is a new approach in designing control algorithms for a large group of robots performing a certain task. In such robotic systems, an individual robot with only limited capabilities in terms of sensing, computation, and communication can adapt its own behavior so that a desired collective behavior emerges from the local interactions among robots and between robots and the environment. Swarm robotics has been the focus of increased attention recently because of the beneficial features demonstrated in such systems, such as higher group efficiency, robustness against the failures of individual robots, flexibility to adapt to changes in the environment, and scalability over a wide range of group sizes.

In this article we present an adaptive algorithm to regulate the behavior of an individual robot performing collective foraging tasks. Through the interactions between robots, a desired division of labor can be achieved at the group level. Robot groups also demonstrate the ability to improve energy efficiency and its potential robustness in different environments.

1. Introduction

Swarm robotics is a relatively new design approach to control a large group of robots in a certain collective task. In such a system, robots can adjust their own actions according to predefined rules with the help of interactions among the robots or between a robot and the environment.

In this article, we study the problem of a group of robots performing a collective foraging task. Collective foraging is a research problem which has often been used in multi-robotics system design. In a collective foraging scenario, a group of robots has to search for objects called "food" that are randomly scattered in a restricted place called the "foraging area." Once it finds food, the robot will take the food back to a certain designated place called "home." Collective foraging is often used as a model for a wide range of real-life applications, such as toxic-waste cleanup, search and rescue, and collection of terrain samples in unknown environments [1].

Concerning acquisition and expending of energy, a group of robots foraging for food will acquire energy from the food they retrieve but will also expend energy on motion during the foraging process. Net energy is the total energy acquired, less the energy cost by the group. The main concern in this study is to determine whether robots are able to cooperate in order to acquire more net energy in a timely manner and also adapt to unknown changes in the environment. Each robot used in this study has only limited capabilities in terms of sensing, computational power, and communication. Due to these limits, a single robot is not capable of knowing the global state of the environment or the overall task progress.

Several considerations can be taken into account in order to increase the net energy of the group. One consideration is the number of actively foraging robots. If this number is too high, since the robots are foraging in a bounded foraging area, interference among the robots not only costs more energy but also decreases the probability of a robot finding food. In addition, more robots actively foraging costs more energy. On the other hand, if the number of actively foraging robots is low, the group might not retrieve enough food energy from the environment. Therefore, there is an optimal value for the number of active foraging robots in a given environment that should maximize net group energy. In order for a robot group to be robust and flexible, this optimal value should be able to adapt to a new value in the changing foraging environment.

Early work [9,10,11] in collective foraging focused on the use of communication design to assess spatial characteristics of the foraging environment in order to coordinate the robots to fulfill the task. Beacon-following methodology characterized the earliest efforts at collective foraging. Scientists have also understood the effectiveness of trail-laying and following in the foraging strategies of social insects, such as ants [5], which provide inspiration for swarm robotic foraging. A large amount of theoretical simulation of trail-based foraging [12,13,14] in robotics has been done.

Recently, there has been increased work in investigating the mechanism of division of labor in collective foraging. Division of labor here means the division of the tasks of actively foraging and resting at "home" among robots in the group so that the net energy income of the group can be optimized. Our motivation for using a division of labor comes directly from the behavior of social insects that we observed in nature. Krieger and Billeter [6] implemented a swarm of up to twelve real robots to demonstrate the efficiency of self-organized task allocation in the performance of a collective foraging task. Labella et al. [2,3] introduced a simple adaptive mechanism to change the ratio of foragers to resters in order to improve the group foraging performance. Jones and Matarić [7] describe an adaptive method for division of labor between collections of two different objects. Guerrero and Oliver [8] present an auction-like task allocation model, trying to determine the optimal number of robots needed for active foraging.

2. Method

We assume the robotic system used in this study is a homogeneous system. All robots in the group follow the same behavior rules in performing the foraging task. The objective is to identify a set of behavior rules for individual robots that could lead to an efficient and adaptive group foraging behavior. The control algorithm is inspired by the mechanism of labor division in social insects. It enables a robot group to achieve a desired division of labor among robots so that the number of active foragers can be optimized. This division of labor can also be dynamically adjusted in response to changes in the foraging environment.

A finite state mechanism illustrating the foraging behavior of the robots is shown in Figure 2.1. It represents the different states of foraging activity in our study.

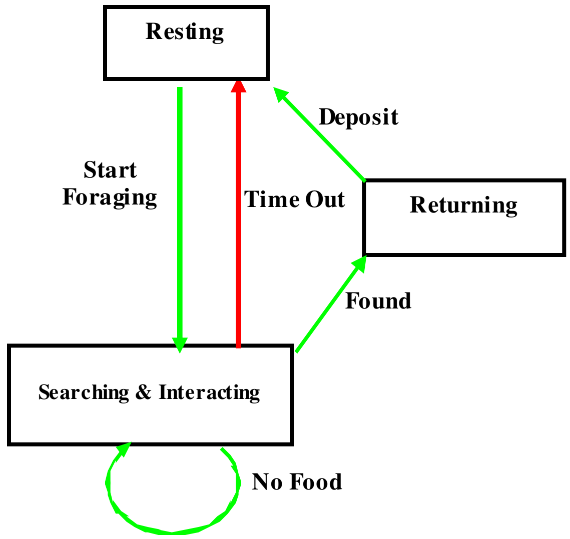


Figure 2.1. State transitions of robot foraging behavior.

The states for robot foraging behaviors are as follows:

- **Resting**: Robot rests at home.
- **Searching and Interacting**: Robot searches for food and interacts when it encounters other robots.
- **Returning**: Robot returns and leaves food at home.

Transitions between states occur on a basis of events that are either external (e.g., food located or time out) or internal to the robot (e.g., deposit). The transitions between the above states are explained as follows:

- **Start Foraging**: Robot leaves home, starts foraging.
- **Found**: If a robot finds food, it grasps the food.
- **Time Out**: If the energy of a robot is used up while the robot still searching, the robot gives up foraging and goes home (failed retrieval).
- **No Food**: Robot has not found food and keeps searching and interacting.

In order to regulate robot behavior so that a beneficial division of labor can be achieved, we introduce the variable foraging probability P for each robot. For example, P(i) is the foraging probability of robot i for which i is the robot ID. Only when P (i) is higher than the threshold value P0 will robot i start foraging; otherwise, robot i will rest at home. Two variables were used to calculate P(i): foraging threshold Th(i) and foraging stimulus S. Th(i) relates to the foraging performance of robot i and S represents the foraging task stimulus for the group. The mathematical model we use here to calculate P(i), as shown in equation (2.1), can be considered an instance of a response threshold model as presented in Bonabeau et al., [4] Thiraulaz et al., [5] and

Labella. [3] In order to explain the division of labor in social insects, Bonabeau has developed a model that relies on response thresholds for each individual. In his model, every individual has a fixed response threshold for every task. Individuals engage in task performance only when the level of task- associated stimulus exceeds their threshold. When individuals with a lower response threshold for performing a given task are withdrawn from the group, less task-related work will be done and the intensity of the stimulus is increased. The stimulus eventually will reach the high response thresholds of the remaining individuals. Theraulaz [14] has extended the fixed threshold model by allowing a threshold to vary in time, following a simple reinforcement process: a threshold decreases when the corresponding task is performed and increased when the corresponding task is not performed. The more an individual performs a task, the lower the response threshold, and vice versa.

$$P(i) = \frac{S^2}{S^2 + T_h^2(i)} \qquad (2.1)$$

Figure 2.2 shows how two variables, Th(i) and S, relate to the P(i) from the equations. The plot is a series of probability curves according to the equation. Each curve has a fixed value of Th along changing S. The graph shows that, with a fixed value of Th, one will have a higher foraging probability when stimulus S increases. Under the same value of S on different curves, a robot with a lower threshold has a higher foraging probability.

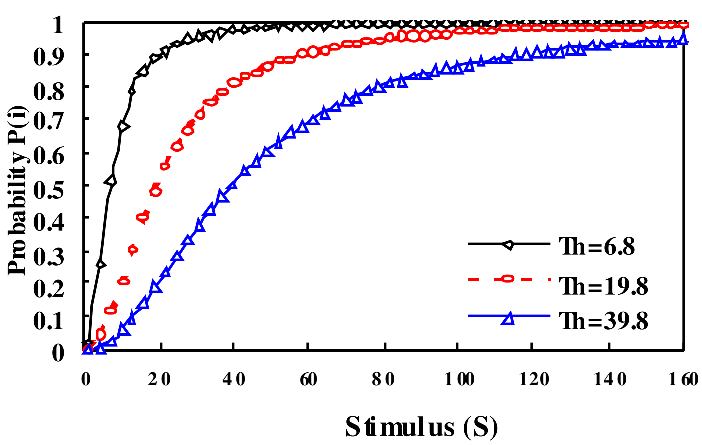


Figure 2.2. Probability curves of response threshold model.

Our division of labor mechanism is inspired by the above response threshold model. It considers both the foraging threshold of an individual robot and environment-related stimulus intensity. We introduce the following adaptation rules to adjust Th(i) and S so that the number of actively foraging robots can be adjusted accordingly.

The adaptation rules are explained as follows:

- **In arena**: when robot *i* encounters another robot *j*, it exchanges foraging state information with robot *j* and records the foraging state of robot *j* in a task counter of robot *i*. The rules are:

Table 1. Adaptation rules for robots in foraging arena

If R_j has already found food, then
TaskCounter(**i**)←TaskCounter(**i**)+1
If R_j is in Searching State, then
TaskCounter(**i**)←TaskCounter(**i**)-1
If R_j is in Fail State, then
TaskCounter(**i**)←TaskCounter(**i**)-2

As long as robot *i* is moving in the foraging field, it keeps interacting and collecting information from other robots. TaskCounter(i) accumulates the information it collects.

- **At home:** Once robot *i* reaches home, it calculates the net energy from the for aging trip to see if it is positive or negative. Positive net energy means successful foraging. Then it updates its own foraging threshold $T_h(i)$ and global foraging task stimulus S according to its own foraging performance and information re corded in TaskCount(i).

Table 2. Adaptation rules for robots at home

A	If R_i Success then
	$T_h(i) \leftarrow T_h(i)-\Delta_1$
	Otherwise
	$T_h(i) \leftarrow T_h(i)+\Delta_2$
	End if

B	If R_i Success and TaskCounter(i)>0, then
	$S \leftarrow S+\Phi_1$
	If R_i Failed and TaskCounter(i)<0, then
	$S \leftarrow S-\Phi_2$

Table 3: Indication

A	"If I am successful, I will increase the probability of foraging again by lowering the threshold. Otherwise, if I fail, I will decrease the probability of foraging again by increasing the threshold."
B	"If I am successful and most other robots that I encountered are successful, there must be a lot of food out there, which increases the stimulus of foraging. If I failed and most other robots I encountered are still searching or failed, it seems there is not much food left, so I will decrease the stimulus of foraging."

Rule A implements the reinforcement mechanism for a robot based on its own foraging performance. Rule B reveals the task stimulus intensity from information collected through the interaction between robots. With the adaptation rules described above, each robot in the group will adapt its own foraging probability $P(i)$according to updated $T_h(\mathrm{i})$ and S. At the group level, the number of active foragers can be automatically adjusted so that group energy efficiency can be optimized.

We have designed a computer simulation program in order to validate the control algorithm presented in the previous section.

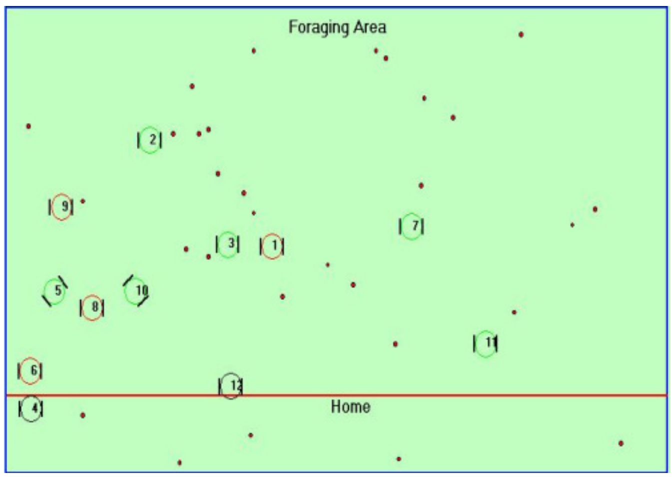


Figure 2.3. Screenshot of the twelve robots foraging

The computer simulator simulates a population of twelve mobile robots foraging for food in a two-dimensional foraging arena. Figure 2.3 is a screenshot of the simulation. The black dots in the blue foraging area represent food. Large circles with numbers inside are mobile robots and their identifying numerals. Different colors on the robots indicate the different states in which the robots presently exist. Red robots have already found food; green robots are still searching in the area; black robots are waiting at home.

3. Experiment Setup

In order to test the hypothesis that the adaptation rules of individual robots can improve the net group energy efficiency and group adaptation ability, a set of experiments was designed which varied the size of the robot group and food density in the foraging area. Two strategies are designed for each type of experiment. In strategy S_1, in which no adaptation rules are used, the system randomly chooses another robot to forage when one robot returns home. The number of active foragers remains at the same value as the group size during the simulation. This provides us a benchmark for comparison. Strategy S_2 uses the proposed adaptation rules to update $T_\mathrm{h}(i)$ and S. The number of active foragers will change over time accordingly.

Before implementing the algorithm, we first need to choose values for the parameters and initial settings. Factors Δ_1, Δ_2, Φ_1 and Φ_2 are applied to update T_h and S. The selection of values of these parameters is based on trial and error. In order to calculate net group energy, we assume one food-unit can bring 4000 units of energy back to the group and the robot would expend sixteen units of energy per second while moving and another fifteen energy units every time it encounters and avoids another robot. In order to return a positive net energy value back to the group, we set a searching energy limit for each robot of 3800 units. Table 3.1 summarizes all of these parameters we have chosen for the experiments.

Table 3.1. Parameter selections for the experiments

Δ_1	Δ_2	Φ_1	Φ_2
0.1	0.05	0.1	0.2

The metric we use to measure the net energy efficiency of the group, called "group energy efficiency," is given below. In this definition, food energy available from the environment is food energy put in the arena by the system over the simulation time. Another metric used to measure the percentage of the available food that has been collected by the group in the environment is called the "collect rate."

$$\text{Energy Effciency} = \frac{\text{Net Group Energy}}{\text{Food Energy Available in Envirnment}}$$

$$\text{Collection Rate} = \frac{\text{Food Acquired}}{\text{Food Energy Available in Envirnment}}$$

4. Results and Conclusions

4.1. Fixed Food Density, Variable Swarm Size

Experiments were designed for group sizes of two, four, six, eight, ten, and twelve robots, respectively. The food growth G_{new} in the experiments is fixed to 2/min, which means the system will place two food-units in the arena every minute. For each group, we apply two strategies and each simulation lasts 200 minutes, which means there are a total of 400 food-units in the arena. We record the number of food-units collected, the number of active foragers, the values of the stimuli and the net group energy. Table 4.1 shows the data we recorded as well as the calculated values from the data.

We compare the food collect rate of the groups using different strategies. Our data show that most groups can reach a high collect rate with the exception of the groups with two or four robots. For the groups with six, eight, ten, and twelve robots, more than 95% of the food is collected no matter which strategy is used. However, the groups with two and four robots collect less than 90% of the food in most cases. Therefore, in order to collect the most food in a given environment, more than four robots are needed in active foraging.

Table 4.1. Simulation results for different group sizes and different strategies G_{new} = 2/min

Group Size	Strategy	Food Collected	Net Group Energy	Average Forager Number	Energy Efficiency (%)	Collect Rate [%]
2	S_1	352	880199	2	55	88
	S_2	309	803890	2	50.24	77.25
4	S_1	324	502590	4	31.4	81
	S_2	371	617646	4	38.6	92.75
6	S_1	394	38297	6	2.3	98.5
	S_2	385	346210	5.27	21.6	96.25
8	S_1	394	-360666	8	-22.5	98.5
	S_2	381	224409	5.72	14.02	95.25
10	S_1	398	-1045025	10	-65.31	99.5
	S_2	389	149153	5.87	9.32	97.25
12	S_1	399	-1622979	12	-101.4	99.8
	S_2	397	81125	6.2	5.07	99.5

Checking the average number of active foragers using strategy S_2 for these experiments, we find the averages are all close to six. All robots are foraging most of the time in the group with four and two robots since there is enough food available for retrieval, and for the group of twelve robots with strategy S_2, the average number of foragers is 6.2. In other words, more than four robots need to be engaged in foraging in order to collect all the food; meanwhile, the more robots resting at home, the more energy the group can save. Therefore in the given foraging environment, in order to maximize the net energy income for the group, the optimal average number of active foragers is close to six. Here, foraging probability in S_2 helps a robot switch tasks between foraging and resting more effectively, allowing the number of active foragers to reach the optimal value. Thus, the overall division of labor in a group (task allocation) emerges from the low-level interactions between robots and the environment.

We compare the energy efficiencies of the groups using different strategies. The efficiency levels are nearly the same in the groups with four robots or fewer, since all robots are engaged in foraging. However, for the groups with more than four robots, the groups with strategy S_2 can always obtain a higher energy efficiency. Figure 4.1 plots the instantaneous net group energy along with time. The net energy gap between S_1 and S_2 increases as the group size grows. Thus we can conclude that, for a large group population, the proposed adaptation mechanisms will not only help the group achieve a division of labor among robots but also will guide the group toward energy optimization in a given environment.

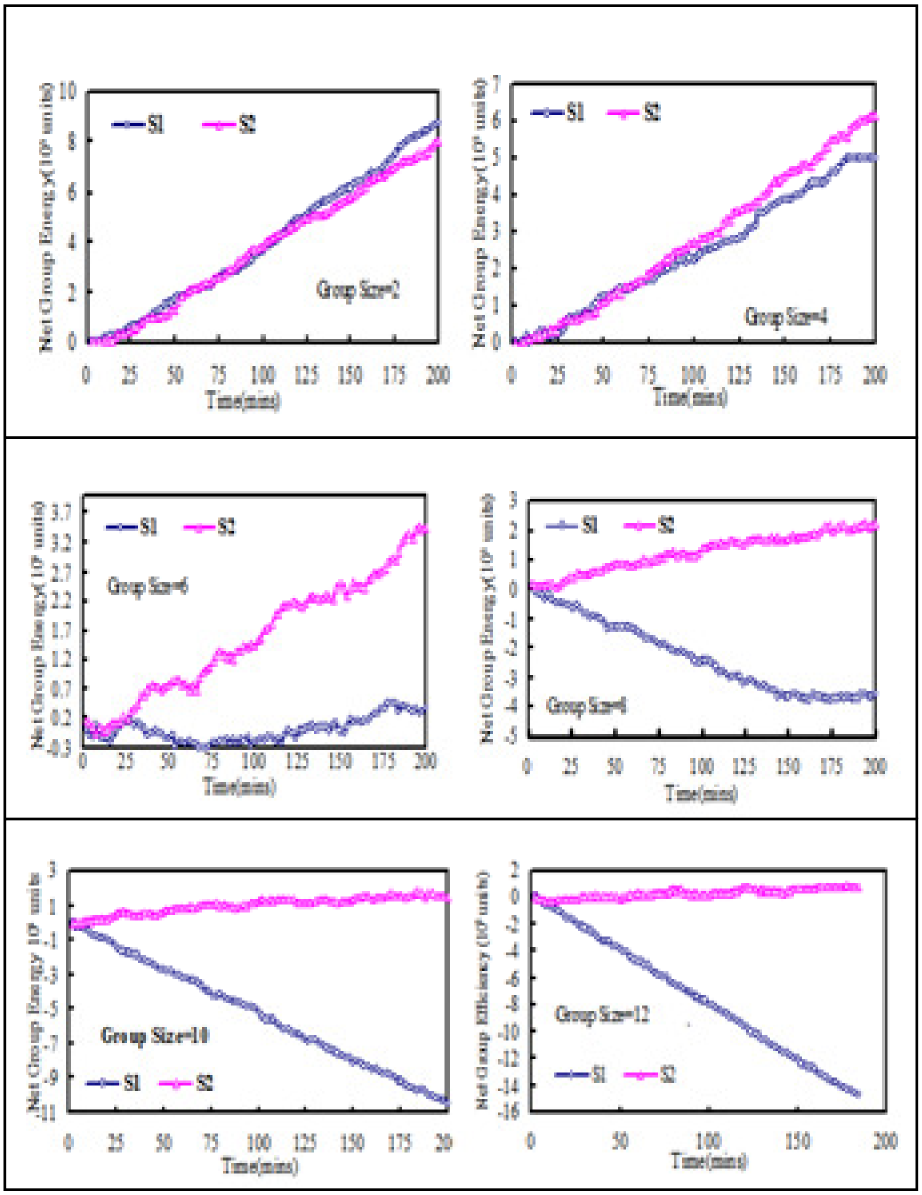


Figure 4.1. Group efficiency of different strategies in different group sizes.

4.2. Variable Food Density, Fixed Group Size

We designed a second set of simulations to investigate how the proposed algorithm can help groups under different environmental conditions; here we fix the size of the group to twelve robots but run the simulations with three different food source densities, from poor (Gnew = 1/min) to relatively rich (Gnew = 4/min). Two strategies S1 and S2 are used for the same group. Data from the simulations are recorded and calculated in Table 4.2.

Table 4.2. Simulation results for same group size under different environment and strategies

Growth Rate(G_{new})	Strategy	Net Group Energy	Average Forager Number	Group Energy Efficiency (%)	Collect Rate (%)
4/min(richer)	S_1	-127218	12	-3.98	99.6
	S_2	666907	10.93	20.84	97.4
2/min(middle)	S_1	-1622979	12	-101.4	99.8
	S_2	81125	6.2	5.07	99.5
1/min(poor)	S_1	-2380534	12	-297.6	99.5
	S_2	-286268	3.61	-17.89	93

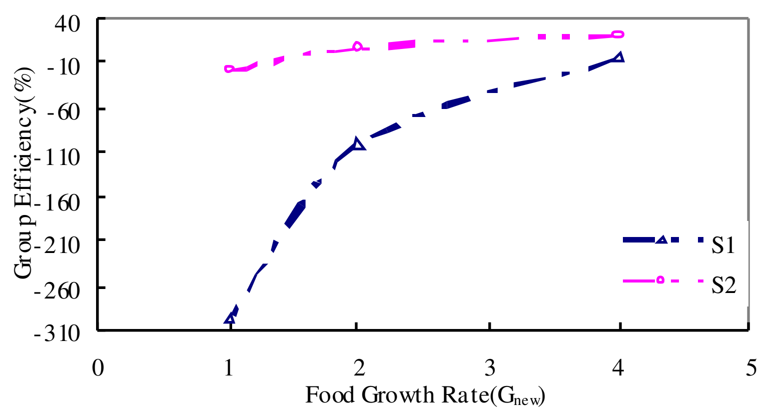


Figure 4.2. Energy efficiency of same group foraging in a different environment.

From the food collect rate, most foods (>95%) are collected by the group no matter what the environment might be, since there are enough robots for foraging. Figure 4.2 plots group energy efficiency changes in different foraging environments. The group with strategy S_2 always has higher net energy efficiency, while the group using S_1 is less efficient in all experiments. The gap between the two strategies becomes smaller in an environment with a higher food density. Despite the food source difference, the levels of energy efficiency for the groups with strategy S_2 are quite stable over different food sources, when compared with strategy S_1, which implies that the group with the adaptation mechanism is quite robust to environmental changes.

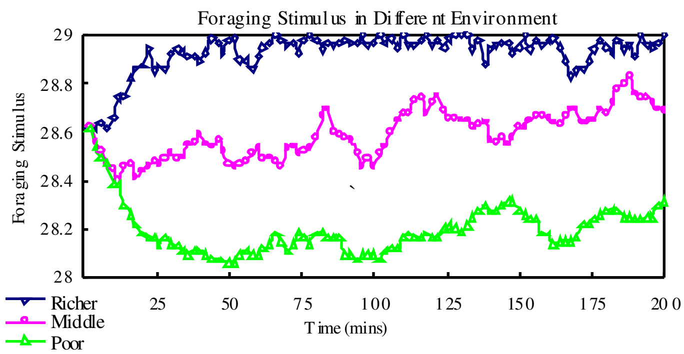


Figure 4.3. Foraging stimulus in different environments.

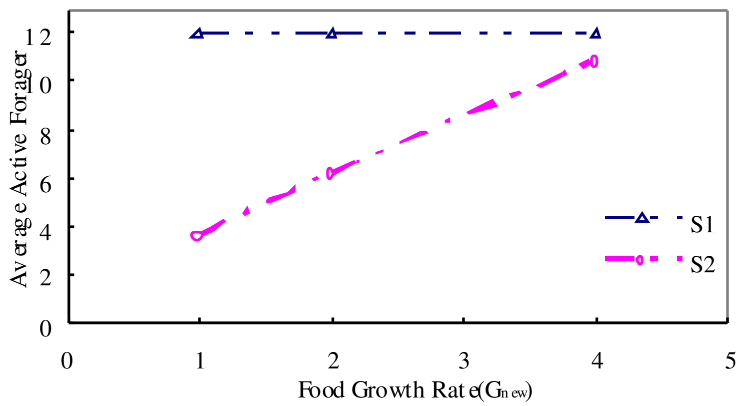


Figure 4.4. Average active forager of same group in a different environment.

Since we used the same group in different foraging environments, stimulus (S) value indicates stimulus intensity from the environments. Figure 4.3 shows that, in a richer environment ($G_{new} = 4$/min), the group has the highest S, and in a poor environment ($G_{new} = 1$/min) group has the lowest S. This means that, through interactions among robots, a group can collectively perceive information about food sources in a foraging environment.

The group exhibits the capacity to perceive the environment collectively if we take into account the average number of active foragers over time. That is, more active robots indicate a richer food environment and more inactive robots indicate a poor food environment. The average number of active foragers under different environments is plotted in Figure 4.4. The average number of active foragers in the group using strategy S_2 is smaller when the food source becomes poorer and bigger when environment become richer. Individual robots cannot know global information about food sources in the environment; this correlation can only be observed at the overall group level and cannot be deduced from individual robots.

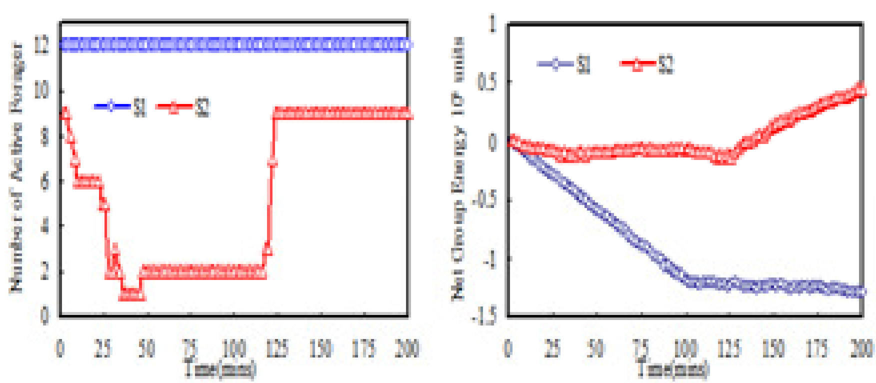
4.3. Dynamic Food Density

We also designed experiments to test whether a group can be adaptive in a dynamic environment. We introduced a step change on G_{new} in the simulations. We ran a simulation which changed a poor environment (G_{new} = 1/min) to a relatively rich environment (G_{new} = 4/min) at time = 100 mins. We plotted the instantaneous number of active foragers and net energy of the group with time in Figure 4.5. As expected, a new dynamic equilibrium for the number of foragers in the group was observed, after some delay, each time the food source density was changed. The group using S_2 adapted rapidly to the change of environment.

In the first stage of the experiment in which robots forage in a relative poor environment, the gradient of net energy decrease for S_2 can achieve less of a decrease than S_1. This shows that the group with the adaptation mechanism is more robust in a worse environment. However, in a richer environment the gradient of net energy for S_2 can achieve a more rapid energy increase than S_1. This shows that the group with the adaptation mechanism can adapt quickly in order to acquire more net energy.

Figure 4.5. Number of active foragers and energy efficiency changes when food growth rate G_{new} from 1/min to 4/mins.

5. Conclusions



In this study, we have designed a set of adaptation rules for a group of robots performing a foraging task. Each robot in the group modifies its foraging probability based on foraging performance (successful or failed food retrieval) and task-intensity-related stimulus through locally perceived information (interactions with other robots during collisions). Division of labor has been achieved in the group. Some robots rest at home for a longer duration to either save energy or to minimize interference, and others are actively engaged in foraging (which costs more energy for the individual but potentially gains more energy for the group).

With the designed adaptation mechanism, the robot group demonstrates:

- Improved group energy efficiency;
- Division of labor between foraging and resting; and
- Adaptation to foraging in a changing environment.

Furthermore, the group also exhibits the ability to perceive the environment collectively if we consider the average number of active foragers over time. That is, more active foragers indicate a richer object environment and more inactive robots indicate a poor object environment. This can only be observed at the overall group level and cannot be received from individual robots.

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