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Adaptive Division of Labor in Multi-Robot System with Minimum Task Switching

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Abstract

In many multi-robot systems, various tasks are allocated dynamically to an individual robot and each robot should decide its own work that is the best commensurate with its current state. To solve complex task allocation problems, agent-based approaches based on the model of division of labor of many social insects have gained increasing attentions in recent years. In this paper, we consider the problem of adjusting the ratio of robots equally to the ratio of given tasks to handle the division of labor dynamically with less number of task switches. Inspired by several insect societies displaying an effective division of labor with the limited abilities, the response threshold model is applied. An Individual robot has a limited, constant-sized task queue and the information obtained from the observation behavior is stored within this queue. Using the ratio of tasks in queue and the predefined response threshold values for all possible tasks, an individual agent decide its task and to handle the desired division of labor dynamically and obtains the specialization for the specific tasks that induces the less number of task switching. To show the robustness and flexibility of our proposed method, various experiments are executed and the results are compared with an other method.

Introduction

Generally speaking, working together can obtain better performance to complete a given task than working alone. Therefore, the concept of swarm intelligence is important to design a cooperation model in multi-agents systems. In multi-agent systems, there are two issues to perform tasks. One is cooperation and the other is division of labor. The focus of cooperation is to achieve a difficult task that a single robot cannot solve alone, and the focus of division of labor is to manage labors efficiently which take lots of times and costs in performing. One approach to these kinds of problems is to establish an appropriate scheduling as an adaptive process that adapts the number of agents that perform the same task in a dynamically changing environment. There are many examples of effective, adaptive behaviors in multi-agent systems and the swarm intelligence has been served as inspiration for multi-agent optimization and control algorithms in recent years.

All individuals in the swarm systems have the same and simple sets of behavioral rules and perform the same activities. However, several insect societies with the limited abilities display an effective division of labor using specialization that different activities are simultaneously performed by specialized individuals (Robinson, 1992). In order to explain these results, the response threshold model where an individual performs a task if the stimulus associated with given task exceeds its threshold is proposed (Theraulaz et al., 1998). An individual with a low response threshold value will tend to perform the corresponding task even if the stimulus is very low. Conversely, an individual with a high response threshold value will perform the corresponding task only if the stimulus is very high. This response threshold model can explain the regulation system of a product, such as food, by allocating individuals to forage as soon as the food demand increases. Examples of division of labor include foraging and nest defense in ants (Detrain and Pasteels, 1991), foraging and nursing (Calderone and PAGE Jr, 1996), and nectar and pollen collection (Visscher and Dukas, 1995) in honeybees.

Individuals can be specialized in a strong or soft manner. Strongly specialized individual only perform one or a few activities. Although genetic factors certainly play a role in some types of strong specialization (Sundstrom, 1995), such as polyethism (age-dependent specialization) and polymorphism (different body shapes), the unpredictable modifications of the environment and the variability within the colony require an additional mechanism to ensuring dynamic task allocation for colony survival. So, the softly specialized individual performs several activities, but tends to perform the activity that is the most needed by the group at every instant. For example, some specialists of type A can carry out task B that they would normally not perform, if the number of specialist of type B decreases (Wilson, 1984).

Task allocations in social insects have been extensively studied since their divisions of labor are realized by simple rules. The fixed response threshold model is an important theory to explain the regulation of division of labor in insect societies based on fixed response threshold value (Theraulaz et al., 1998). This model generates the different response depending on the intensity of a stimulus and the response threshold value and determines the tendency of an individual to a particular task. Task allocation problem based on the fixed response threshold model was studied to deal with labor regulation (Yang et al., 2009). Furthermore, an improved version that dynamically adapts threshold values has been studied. A computational model of how wasp colonies coordinate individual activities and allocate tasks to meet the collective needs is proposed in study of (Cicirello and Smith, 2004). In the study of (Lichocki et al., 2012), the response threshold model is represented by the artificial neural networks and provides a mechanism to regulate division of labor in social insects. However, the method such as neural net or genetic algorithm is not suitable in a distributed system and if we approach in a centralized system, all information is shared among the robots and an individual robot knows the ratio of entire tasks, then robots can choose its own behaviors easily as the fraction of tasks. In our work, the entire information is not available to an individual robot and it is nature to use the local knowledge alternatively to achieve the effective division of labor.

In this paper, we consider the problem of dynamically adjusting the ratio of robots equally to the ratio of given tasks with less number of task switching. Task switching needs a non-productive period of time which is used to be ready for processing the different type of current task and may need additional costs in many factory applications, so it is recommended to reduce task changes for improving the performance of system. In the following sections we will describe our task and simulation results display the robustness and adaptability to environmental variations of our proposed model.

Task Description

The important part of swarm system is surely how to measure the overall performance of multi-robot system. In this paper, the way of checking the performance of system is used by foraging task as shown in the paper of (Jones and Mataric, 2003). One of two kind of colors is assigned to robots and each robot performs a task to forage the closest puck whose color is same with the its current assigned color. Simultaneously, robots perform avoiding obstacles for preventing collision with other robots and barrier of a circular arena, and change its current color if necessary. Especially, this task is seen as a feeding behavior of animal swarm if robots and pucks are regarded as predators and prey, and the performance is determined by counting the number of foraged pucks and the number of task changes among all robots. In many studies, the foraging tasks are commonly selected to search for a specific object and move it properly to any storage place such as home or nest. However, robot generally spends lots time for wandering in that case. Thus, the task is set to detecting pucks and not to move them to handle the division of labor more accurately and quickly.

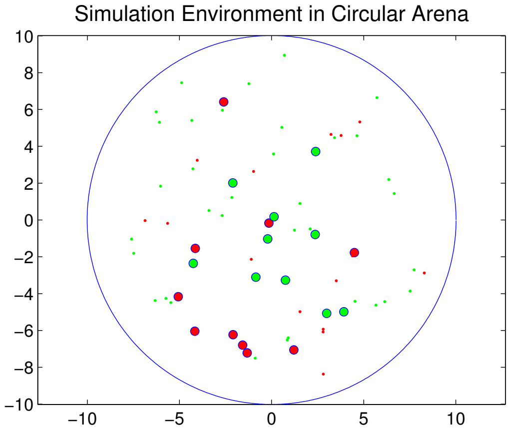

Figure 1: Snapshot of simulation environment. Robots and pucks are distributed randomly in a circular arena. The dark (red in web site) and light (green in web site) gray circles are robots that move randomly in an arena and the small dots are pucks to be foraged by robots.

Simulation Environment Setting

Foraging task is performed in a circular arena and the simulation environment is shown in Fig. 1. The area of arena is about $315m^2$ and the radius is about $10.01m$. Initially, robots and pucks are distributed randomly in an given arena and assigned to red or green color in a specific ratio. As time goes on, the robots move randomly and if the robots detect and grasp the pucks, new pucks which are the same color of foraged pucks are generated in arbitrary places. These relocations mean maintenance of the number and ratio of pucks that there are dynamically additional works from viewpoint on foraging task.

Robot Behaviors

Each robot notices surrounding situations through its sensors and decide the task based on the local information. The robot finds the closest puck whose color is same with the assigned color and turns toward the direction of the selected puck location and moves to grasp the puck. The robot behaviors are composed of camera detection, wandering, obstacle avoidance, grasping, and color switching. The details of the behaviors are explained as below.

Camera Detection Each individual robot has a camera which shoots the front of 60° with $5m$ range and obtains the information about how many and how far red and green pucks are located using visual information. The robot stores the obtained information in its task queue and estimates the desired ratio of puck colors by counting the number of puck colors in the queue at the color transition stage. Because the continuous scanning shows duplicated results and produces poor estimations of the desired ratio of tasks, the robot's camera shoots at every $2m$ movement.

Wandering We used circular robots which is $30cm$ in diameter. The maximum forward/backward speed of robot is set to $0.25m$ per each simulation time step and robot can rotate at the same spot. Robot moves after the preceding camera detection is finished, but does not carry out wandering behavior if obstacle avoidance or grasping puck is performed.

Obstacle Avoidance Obstacle avoidance is the basic and important behavior of swarm robots to remove the collision accident with other robots or obstacles. The barrier of arena and other robots are defined as obstacles, but the pucks are not regarded as obstacle. If the obstacle avoidance is performed frequently, the robot spends lots of time on avoiding behavior and wandering or grasping behavior is not carried out in that time step, therefore accidents between robots and pucks are ignored.

Each robot has 8 IR sensors and sensors are equipped on the border and distributed uniformly so as to cover $180°$ on the front side of robot. The range of sensor is $1m$ and robot changes moving direction when any objects are detected within this sensing range. A robot turns right when the left part of sensors detect obstacles, and the robot reversely turns left when the right part of sensors detect obstacles. The amount of turning angle is set to $45°$ in these two cases. If both parts of sensors detect obstacles at the same time, the robot heads toward the counter direction by turning half rotation. So, the basic turning angles are set to $45°$ and $180°$. However, if the amount of change is same, the changing pattern is same and there is a danger of congested traffic when the robots are surrounded in a specific area. Thus, we add the difference in angle with Gaussian random variables for avoiding these problems.

Grasping Robot finds the closest puck of same color and adjusts the direction toward the closest puck. If the distance between the robot and the selected puck is lower than $0.5m$ and there is no occurrence of obstacle avoidance, the robot grasps the puck. After grasping puck, robot moves to other place to forage next pucks.

Color Switching Each robot has to decide what color of puck it forages. Each individual robot has a limited, constant-sized task queue and the local information obtained from the observation behavior is stored within this queue. Each individual estimates the ratio of tasks in its queue and updates task switching function using an estimated ratio of tasks and the response threshold values for all possible tasks. Robot can change its current task probabilistically based on the score value of task switching function and performs the task that has the maximum score value. Through these repeated behaviors, each robot becomes to have a tendency to process one specific tasks, and this specialization reduces the total number of task switching with maintaining the desired global division of labor.

We propose the following task switching function based on the estimated ratio of puck colors stored in task queue and the predefined response threshold values for tasks.

$$P_{\theta_{ij}}(t) = \frac{S_{ij}(t)}{\theta_{ij}} \tag{1}$$

Eq. (1) indicates the score value for ith robot about jth color at time t and is determined by the estimated ratio $S_{ij}(t)$ and the response threshold value θ_{ij}. As the estimated ratio is measured higher or the threshold value is lower, this score value is computed higher, and robot changes the current color to the color that has the maximum score value.

If the length of the queue is increased, the estimated results will be more accurate and the change rate of the stimulus becomes smoother. Then, the number of task switching will be decreased. Considering these effects of queue length, two formulations for estimating the ratio of puck colors are proposed. The first method (called $'History1'$) is based on the moving average of the information deposited by the queue, and the second method (called $'History2'$) is based on the moving average of the value obtained from the first method. In the first approach, the estimated puck ratio $S_{ij}(t)$ is obtained by the following equation:

$$S_{ij}(t) = \frac{1}{N}\sum_{l=1}^{N} color_{ij}{}^{l}(t) \tag{2}$$

with N is the length of task queue and $color_{ij}{}^{l}(t)$ is 1 if the puck color in the lth queue of robot i is color j at time t, otherwise 0. In the second approach, the stimulus $S_{ij}(t)$ is obtained by following equation:

$$S_{ij}(t) = \frac{1}{N}\sum_{k=0}^{N-1} S_{ij}(t-k) = \frac{1}{N}\frac{1}{N}\sum_{k=0}^{N-1}\sum_{l=1}^{N} color_{ij}{}^{l}(t-k) \tag{3}$$

This second method has an effect to have a NxN length of the queue and N is set to 20 in this paper.

On the other hand, every robot initially has randomly distributed fixed response threshold values for two tasks of foraging red and green color pucks. Each threshold value has a range from 0 to 1 and the sum of two values is set to 1. These fixed response threshold values are enough to handle the division of labor. Through these variations of response threshold values, the results of Eq. (1) are different about the same estimated ratio of puck colors and this specific choosing phenomenon is enough to be called as specialization about the particular color. This phenomenon affects the performance of system by reducing task changes. Therefore, the division of labor considering specialization is shown well in this simple model. Closest to our work, the ratio model studied two different kinds of foraging task switching functions, such as simple step and probabilistic transition function using ratio of pucks and foraging robots (Jones and Mataric, 2003). However, our model differs in using a task switching function based on the response threshold model.

Experimental Results

We evaluate our model by counting the total number of foraged pucks and the number of task changes in all robots. There are 50 pucks distributed and 20 robots move around to find pucks. Initially, the first half of robots are assigned to red color to forage red color pucks and the others robots are assigned to green color to forage green color pucks. The ratio of pucks is changed during simulation to check the robustness and adaptability to the environmental variations. During the first 1000 simulation time steps, the ratio of red and green color pucks is set to 30% vs 70%, respectively. 15 red pucks and 35 green pucks are randomly distributed in a given arena. After the first simulation period, the ratio of red and green pucks is changed to 80% vs 20%, and 50% vs 50% at every 1000 simulation time steps passing. The performances of 20 independent runs are averaged and the different positioning of robots and pucks and different values of response threshold are all selected randomly at every trial.

Fig. 2 and Fig. 3 show the results of foraging task simulations using different task allocation algorithms. The dash-dot line represents the result of ratio model, the dotted line

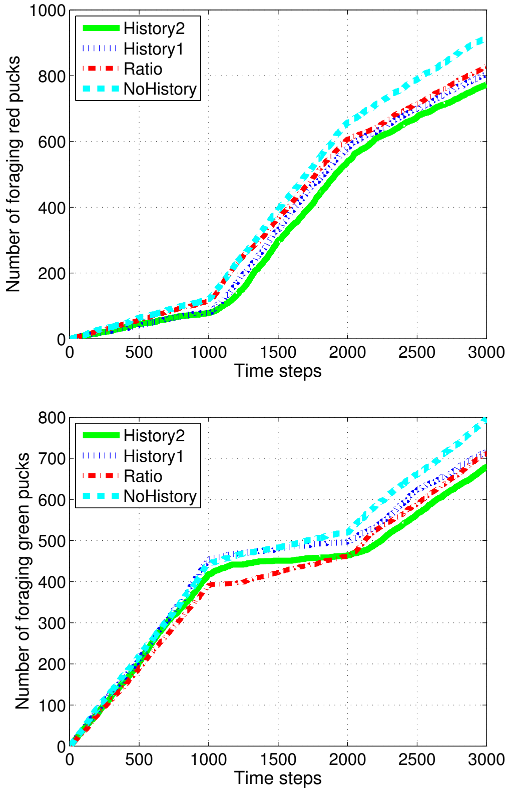

Figure 2: The total number of foraging red (top) and green (bottom) color pucks. The dash-dot line (red in web site) is the result of the ratio model, the dotted line (blue in web site) is the result of *'History1'*, and the solid (green in web site) line is the result of *'History2'*. The dashed (cyan in web site) line is the result of *'History1'* with no task queue.

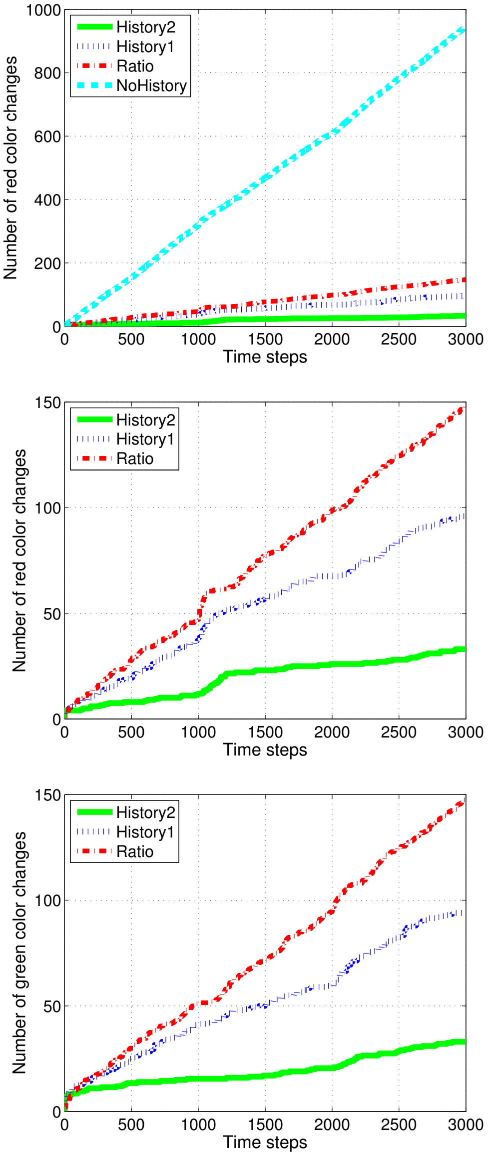

Figure 3: The total number of task changes for red color in all models (top). The number of task changes for red (middle) and green (bottom) color in three models that use task queue.

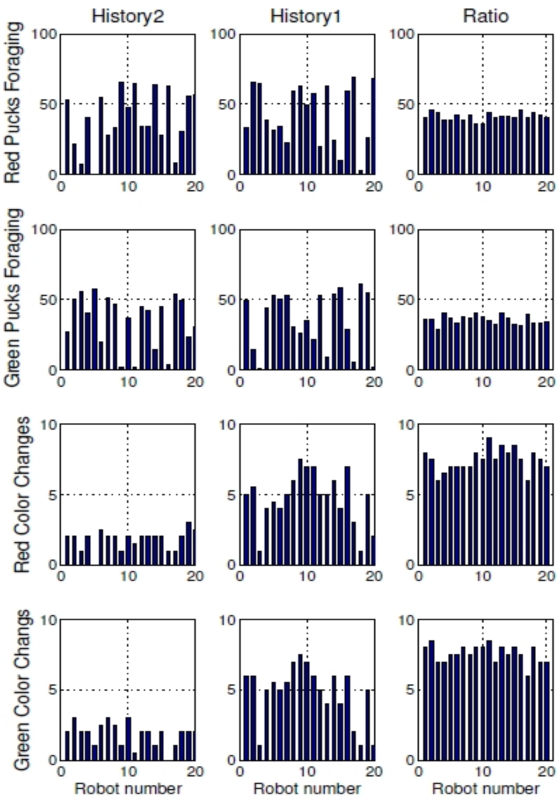

Figure 4: The detail performance of individual robot. The first column is the results of *'History2'*. The figures in the second and third columns are results of *'History1'* and ratio model. There are number of foraging red and green color pucks, color changes for red and green color of all robots from top to bottom direction, respectively.

is *'History1'*, the solid line is *'History2'*, and the dashed line is the result of *'History1'* with no task queue. The red and green pucks are foraged steadily with the similar rate in all methods, and the number of color changes of all robots are reduced to 65.2% of red colors and 63.5% of green colors in the results of $'History1'$, and 22.3% of red colors and green colors in $'History2'$ comparing to the results of ratio model. The model that doesn't use the task queue shows many times larger of color changes than other models that use the task queue.

Our model based on the response threshold model, especially *'History2'* shows the significant performances in reducing the task changes, and the specialization characteristics of robots is the most important attributes in these results. If robot starts to forage one specific color intensively, the robot is designed to have a tendency to forage the same color puck, even if the same amount of stimulus intensity is induced by each color. The specialization for an individual robot and the performances of each robot can be compared in Fig. 4. The most striking feature is a task specialization. All robots in the ratio model forage red and green pucks equally, but the pucks are foraged selectively in our models. Relying on the difference of the response threshold values for two colors, some robots are strongly specialized in foraging a specific color puck. For example, in the result of *'History2'*, the robot 9, 11 and 16 foraged almost red color pucks and the robot 3, 5, and 17 foraged almost green color pucks, so there are few color change occurrences among these robots. However, other robots that are softly specialized forage both color pucks and the major of color changes occur among softly specialized robots.

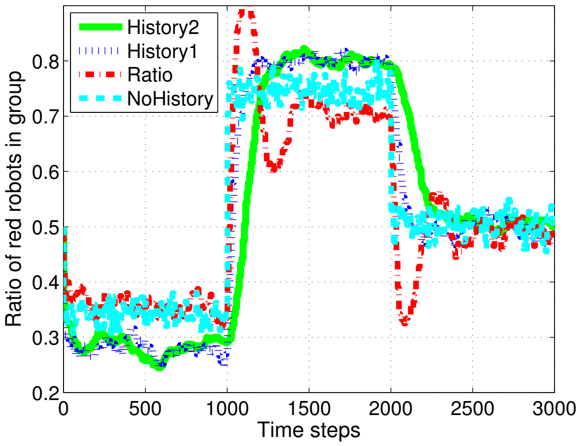

Figure 5: The overlapped trends of ratio of red color robots in group. In foraging task, the ratio of red color pucks is set to 30% initially and the ratio is changed to 80% and 50% after every 1000 simulation time steps.

In general, the shorter length of task queue results the fast convergence to the desired division of labor but leads to more frequent task switching for an individual agent. The Fig. 5 shows the ratio of red color robots in group during the entire simulation. From the results, we can see that $'History1'$ shows the faster convergence to the desired ratio than $'History2'$. However, there are some differences in the results of the ratio model. The ratio model shows the fastest response to changes of environment, but it shows the worst overshooting and errors to the desired ratio of the red color robots. The ratio model focuses on matching between the estimated ratio of puck and the color ratio of robots. So, even in an extreme case, the ratio model sets a few robots to foraging the minor color pucks. It can be seen as the waste of robot resources because it is better to foraging the major portion of color pucks, but this leads to better results in foraging the minor portion of color pucks in a circular arena. This trade-off will be discussed in the next section. On the other hand, $'History1'$ with no task queue converges immediately and slightly off of the desired division of labor.

Discussion

The multi-robot systems can be applied to various tasks and the performance of system is not easy to be defined in multi-criterion objectives. There are many variables considered in foraging tasks. For example, the results can be evaluated as the wasted time for completing tasks, consumed energy, actual amount in a division of labor, the number of foraging pucks, and the number of task switching.

If we consider the total wasted energy as the performance of system, an individual robot can spend energies for camera detection, grasping a puck, wandering distance and color change. The number of camera detections and grasping pucks are proportional to the simulation times and the wasted energies for those behaviors are not much different for all methods. In addition, the total number of wandering distance is also same as shown in Fig. 6, then the total consumed energies depend mainly on the number of task changes. So, the difference performance between the response threshold model and the ratio model will stand out if there needs some extra cost in a task switching. As the occurrences of task switching are frequently, the totally consumed energies for foraging pucks are increased more rapidly in the ratio model and the response threshold model is more appropriate when the transition cost is high.

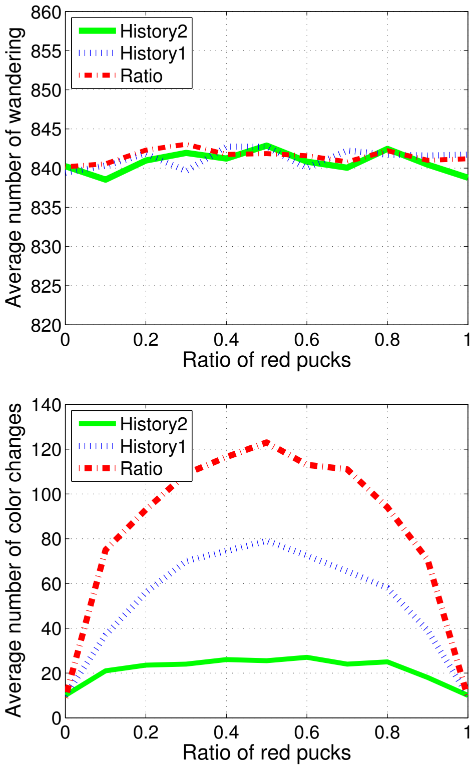

Figure 6: The number of wandering (top) and color changes (bottom) according to the ratio of red color pucks from 0% to 100% during 1000 simulation time steps. The number of wandering is almost same, but the number of color changes differs according to methods and ratio of red color pucks.

The performance will be also changed if the ratio of puck colors is different. If the ratio of one specific color is high, the probability that the robot meets pucks of the same color is also high. It means that the number of task switching becomes smaller in that case and this leads to the improvement of result. Based on results in Fig. 6 which shows the number of color changes according the ratio of one specific color pucks, it is easy to think that both ratio model and response threshold model will show improvements as the ratio of major portion puck is increased.

However, the system is difficult to be always good at all cases when it shows high performances in some aspects. If we concern the ratio of foraging pucks as the performance of forging task, our models show the worse performance. This is because the distribution of pucks in a circular arena makes the difficulty for robots to search specific color pucks and produces difference between the ratio of red robots in group and the ratio of foraged red pucks. In the response threshold model, the robot becomes to have a specialization and tends to forage one specific color puck. So, the moving distance without task changes of robots become longer and the probability that robots meet the wanted color pucks is decreased as the square of ratio in a circular area. Especially, if the portion of two color pucks is much different, the minor color pucks have a little chance to be foraged by robots.

Fig. 7 shows the significant difference in the results of the number of foraged pucks during the first 1000 simulation time steps in Fig. 5 when the ratio of red color pucks is set to 30%. The number of foraged green color pucks is larger and the number of foraged red color pucks is smaller in the response threshold models than that of the ratio model. Theoretically, the probability that robots can find specific color pucks in a circular arena is proportional to the square of ratio of each task. When the ratio of red and green color pucks is 30% vs 70%, the probability that robots meet red color pucks is 9% / (9% + 49%). If there are no obstacle avoiding behaviors, then the theoretical ratio of foraging red puck is 15.5%. In Fig. 7 *'History1'* and *'History2'* tend to converge slightly off of the expected ratio.

Conclusions

The division of labor generally needs the entire information of environment as an important variable. However, in many multi-robot systems, robots don't have enough knowledge about environment and each robot should use its local observation knowledge alternatively and choose the best commensurate work with its current state. In this work, we applied the response threshold model to foraging task and obtained a division of labor for performing a given foraging task more effectively. Our proposed model based on the estimated task ratio as an important variable and randomly

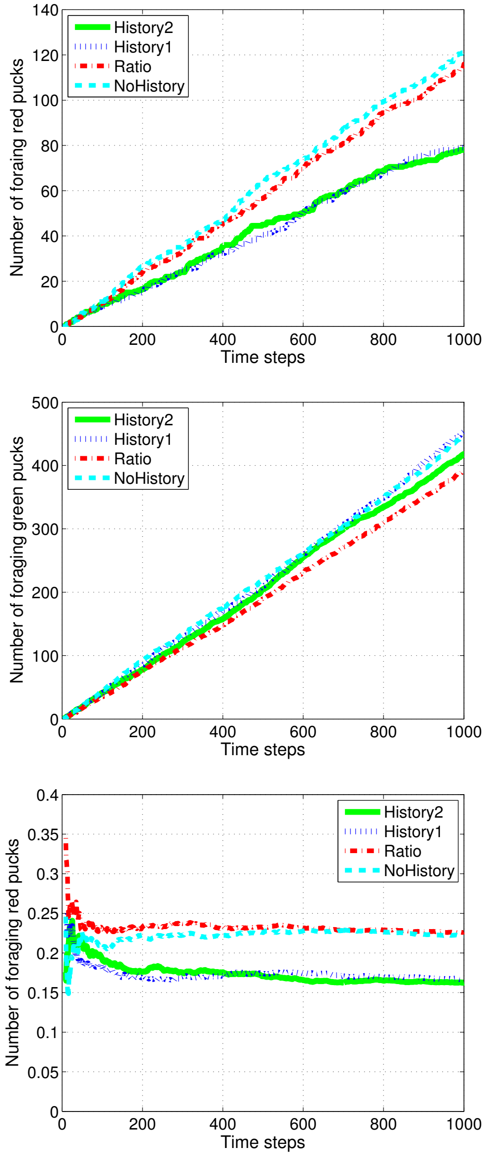

Figure 7: The total number of foraged red color pucks (top), green color pucks (middle) and the ratio of foraged red color pucks during the first 1000 simulation time steps in Fig. 5 when the ratio of red color pucks is set to 30%.

selected response threshold values for all tasks displays robust and optimal results. Fixed threshold values are enough to have a specialization tendency of robots and the overall performance of system has an advantage in minimizing the occurrences of task switching. If there needs extra costs for task switching, our method will shows an improved energy efficiency. However, we observe that there is a little trade-off between the number of foraged pucks and color changes in a foraging task using a circular arena. We will apply to various problems to check the robustness and flexibility of our method. Moreover, there are many other variables to be measured as the performance of given task and we leave the works as a future work. Furthermore, we will study automatic methods for selecting the optimal number of groups having the same response threshold values or the optimal response threshold values for each group to reduce the task changes with maintaining the ability of division of labor.

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