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Immune Based Task Allocation Method for Multi-Robot System

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Abstract: To efficiently accomplish unknown tasks in the multi-robot multi-task system, an efficient task allocation method and autonomous cooperation among robots are required. This paper fully takes advantage of the interactions among antibodies and antigen stimulus of immune system to solve the problem. Firstly, a new artificial immune network (AIN) model is proposed for the multi-robot system based on the principles of the biological immune system. Based on AIN model, the multi-robot task allocation algorithm is designed by utilizing the interactions among the antibodies, and the event-triggered task reallocation is adopted to realize the dynamic task allocation. Then the dynamic task allocation method is developed and extended by integrating the cooperative idea into the antigen stimulus. By the self-reinforcement learning of the antigen stimulus, the autonomous cooperation among robots is realized and deadlock situation is avoided. Based on the committed/opportunistic attribute of the robots, three different methods are proposed to implement the autonomous cooperation among robots. In the simulation and discussion, the immune based allocation method is further analyzed from the communication and computation aspects and is verified. And in the experiment of autonomous emergency handling, the three integration methods are validated, studied and compared.

Keywords – the artificial immune system, task allocation, autonomous cooperation

1. INTRODUCTION

In the field of cooperative multi-robot systems, task allocation is one of the fundamental aspects receiving much attention, such as negotiation method [1], marketing method [2], and MURDOCH method [3]. However, most of these methods are classified as greedy algorithm, which focuses on a single robot's performance and results in degrading the overall performance compared with the optimal one [4]. To find a better task allocation strategy becomes quite necessary. This paper proposes an immune based task allocation to implement the effective allocation.

There has been significant research in multi-robot coordination [5,6,7]. But as indicated [8], the limitation of current cooperation systems is the lack of the capability to autonomously decide that how many robots should work together for each task without prior knowledge of the tasks, which we call autonomous cooperation [8,9]. To

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accomplish unknown cooperative tasks by multi-robots, especially in hazard environments, an efficient task allocation method and autonomous cooperation among robots are required. An appropriate task allocation method is required to allocate the robots to unknown tasks in an adaptive and flexible way. Such capability is essential and necessary for multi-robot system in new or hard environments. And it is also one criterion of the environmental adaptation for the multi-robot system. However, common allocation methods can't meet the demand well. This paper fully takes advantage of the interactions among antibodies and antigen stimulus of immune system to solve the problem. The goal of this paper is not only to realize autonomous cooperation, but also to increase working efficiency by integrating the cooperation with task allocation.

The remainder of the paper is arranged as follows. Section 2 proposes an Artificial Immune Network (AIN) model for multi-robot system. Section 3 describes the static and dynamic multi-robot task allocation algorithm fully utilizing the interactions among antibodies. In section 4, the dynamic task allocation method is developed for autonomously cooperative robots by integrating the cooperative idea into the antigen stimulus. By the self-reinforcement learning of the antigen stimulus, the autonomous cooperation among robots is realized and deadlock situation is avoided. Three methods are proposed to realize the integration of the autonomous cooperation and dynamic task allocation. Section 5 is simulation and discussion, where the allocation algorithm is further analyzed. And the three methods are validated, studied and compared respectively in the experiment of emergency handling. Our conclusion and the future research will be presented in section 6.

2. ARTIFICIAL IMMUNE NETWORK (AIN) MODEL

The original idea of robot construction is to simulate the human intelligence and in turn, the intelligent characters of the biological systems have always been the objects that robot systems simulate or learn from. In the natural world, the animals defend the foreign invaders and maintain the balance of the biological world by cooperation. Here we try to apply the working mechanism of the biological system to the multi-robot system. Imitating biological systems, several novel computational methodologies have been produced such as genetic algorithm, neural network and immune engineering that are useful in solving complex engineering problems.

2.1. Overview of the biological immune system

AIS (Artificial Immune System) is a simulation of the biological immune system. It is expected to be a potential research subject with powerful information-processing ability. The protection system that eliminates foreign substances is called immune system [10].

The basic components of the immune system are lymphocytes that exist as two major types, B cells (B lymphocytes) and T cells (T lymphocytes). The immune system recognizes and kills the invading foreign substances, which is called antigens, by emitting various lymphocytes.

As Jerne pointed in the "idiotypic network hypothesis" [11]: B cells produce various antibodies. The portion on the antibody that recognizes the antigen is called paratope, and each type of antibody also has its specific antigen determinant called idiotope, which can be recognized by paratope. If the paratope of the antibody recognizes the antigen or other idiotope part, the antibody is stimulated. On the contrary, if the idiotope of the antibody is recognized by other paratope part, the antibody is suppressed. When the antigens invade the system, the balance is destroyed. The imbalance triggers the antibodies to stimulate or suppress each other, and proper antibodies are chosen to kill the antigens autonomously. Then a new balance is built again through the interaction chains. This model has been the most popular model of AIS.

2.2. Immune based AIN model

Many researchers have studied the artificial immune model based on the biological immune mechanism. For the biological immune system has the fully distributed architecture, the autonomous decision-making mechanism and the capability of dynamic balancing, this paper proposes a new AIN model for multi-robot system based on Jerne's hypothesis.

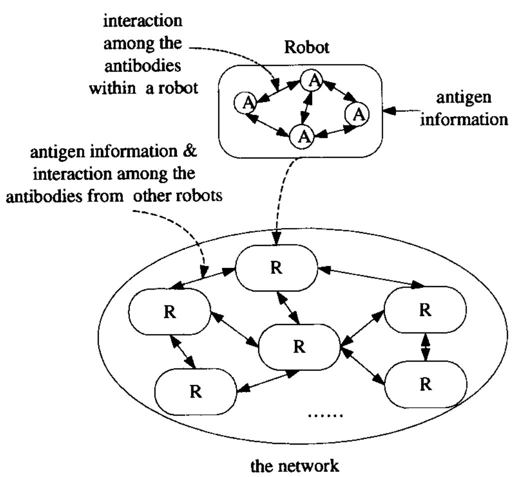

Figure 1. Network structure of the AIN model

This paper proposes an AIN model as shown in Fig.1, where the system is composed of n roots indicated by 'R'. The task is simulated as antigen and each robot as B-cell. And antibody (indicated by 'A') produced by B-cell is regarded as a robot being able to perform a task. Therefore, the antibodies are classified into two types: within a robot and from different robots. Fig.1 describes the network structure of the whole system, which mainly focuses on two parts. 1) Intra-robot: the antigen information sensed by the robot and interaction among the antibodies within the same robot. 2) Inter-robot, between the robot and other local robots in the network: including the communication of the antigen information and the interactions among the antibodies from different robot. Here the intra- and inter-robot efforts establish and maintain a large-scale network.

For current research based on the immune system, single-robot systems focus on the first part [12] while multi-robot systems mainly consider the second part [13]. The mutual-coupled immune network hypothesis [14] was an exception, which considered the two parts together. However, in mutual-coupled immune network, the interaction among LINs was regarded as coordination antigen and the interactions among antibodies are not fully utilized in the algorithms. Our AIN model tried to exploit the interactions among antibodies and integrate the two kinds of interactions for task allocation.

The AIN model can be formally described as 4-tuple

$$AIN=\langle R, T, ANB, REL\rangle \tag{1}$$

Where R is the robots, T is the tasks, ANB is the antibodies produced by B-cells (robot), REL is relations between antigen (task) and antibody, and among antibodies.

The robots and tasks are described as

$$R=\langle R_1, R_2, \ldots R_i\rangle \tag{2}$$

$$T=\langle T_1, T_2, \ldots T_j\rangle \tag{3}$$

The antibodies are described in Equation (4), where $anb(R_iT_j)$ is the antibody generated by R_i for T_j. They are classified as inter-robot (ANB_{inter}) and intra-robot antibodies (ANB_{intra}), for each robot can produce different antibodies for antigens.

$$ANB=\langle anb(R_1T_1),anb(R_1T_2),\ldots anb(R_iT_j)\rangle \tag{4}$$

$$ANB=ANB_{inter}\square ANB_{intra} \tag{5}$$

$\langle anb(R_mT_p), anb(R_nT_q)\rangle \square ANB_{inter}$ means $m\neq n$, and the two antibodies are generated by different robots, otherwise from the same robot.

REL is the relations among antigen and antibodies.

$$REL=\langle STI, INT\rangle \tag{6}$$

STI is the relations between antigens and antibodies. And g_{ij} is the antigen stimulus for $anb(R_iT_j)$. If R_i have no ability to perform T_j, $g_{ij}=0$.

$$STI=g_{ij},\ antigen(j) \longrightarrow anb(R_iT_j) \tag{7}$$

INT is the interactions among antibodies, including stimulation and suppression.

$$INT+= anb(R_mT_p) \xrightarrow{+} anb(R_nT_q) \tag{8}$$

$$INT-= anb(R_mT_p) \xrightarrow{-} anb(R_nT_q) \tag{9}$$

$\xrightarrow{+}$ means stimulation, and $\xrightarrow{-}$ is suppression.

The whole network works as shown in Fig.2 (R_i as an example): For different tasks including sensed by robot itself or transferred from other robots, R_i generate corresponding antibodies, like anb(R_iT_1), anb(R_iT_2), anb(R_iT_j). And the antibodies get the antigen stimulus from corresponding tasks, which could include all relevant aspects of the state of the robots and their environment. For the antibodies are classified into two parts, from different robots and within a robot, the interactions among the antibodies also include the inter-robot action, which are among the antibodies from other robots, and the intra-robot action, which are among the antibodies from the same robot. Based on the antigen stimulus and interactions among antibodies, each antibody appears the different concentration. Antibody with highest concentration value of each robot is activated, and the robot chooses to perform the corresponding task.

Based the AIN model, the architecture of the system is fully distributed and each robot autonomously chooses the action based on the local antigen information and interactions among antibodies. At the same time, the system is coordinated through communication and the interactions, and comprises a stable network. Compared with other models based on the immune system [12-14], our model provides a formal description, integrates the interactions among the antibodies from inter- and intra-robot together, and accomplishes the task allocation autonomously.

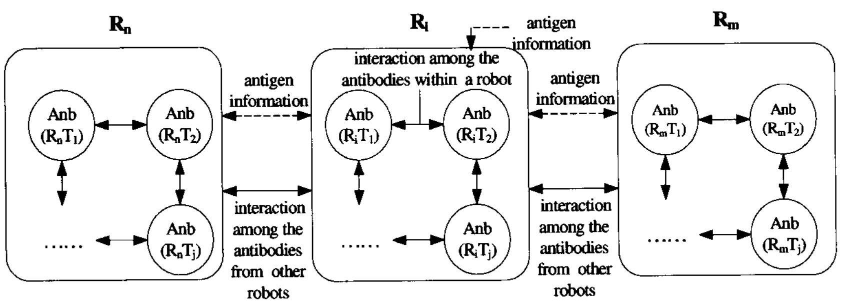

Figure 2. Schematics of the AIN model

3. TASK ALLOCATION ALGORITHM

The multi-robot system based on the AIN model is distributed and behavior-based. Each robot chooses tasks autonomously based on the environment and interactions among other robots. When an allocation conflict occurs, robots cooperate to solve the conflict by interaction and communication. Robot can totally work independently even other robot fails.

3.1. Immune-based static allocation algorithm

Applying the AIN model to the multi-robot task allocation, the antigen information refers to the task information. The corresponding antigen stimulus g_{ij} indicates the capability for the R_i to perform the T_j. The interactions among the antibodies can be divided into two parts: a) inter-robot action. When many robots choose the same task, the antibodies for this task are generated by these robots, and the inter-robot actions are among these antibodies (ANB_{inter}); b) intra-robot action. A robot may have the ability to perform many tasks, and generates corresponding antibodies. Intra-robot action is produced among these antibodies (ANB_{intra}).

Taking R_2 for example, we describe the specific algorithm:

1) Based on the distributed architecture, R_2 and other robots respectively choose the tasks with maximal antigen stimulus value as their optimal one. The antigen stimulus could include the relevant aspects of the state of the robots and environment. Here we simply set

$$g_{ij} = v_i / d_{ij} \tag{10}$$

where v_i is the speed of R_i, and d_{ij} is the distance between R_i and T_j. We will further adjust g_{ij} in Section 4. We set anb(R_iT_{opt}) as the antibody generated by R_i for the optimal task T_{opt}. If no other robots choose the same T_{opt} as R_2, anb(R_2T_{opt}) is activated for the antigen T_{opt}, and T_{opt} is directly allocated to R_2, otherwise go to step 2.

2) If some other robots choose the same optimal task Topt as R_2, action should be taken to solve the conflict. Here D is the set of robots that choose T_{opt}. Each robot R_i in D then generates the anb(R_iT_{less}) for their less optimal tasks T_{less}. What's the interactions (INT) among the antibodies (anb(R_iT_{opt}), anb(R_iT_{less})) is quite important.

For anb(R_2T_{opt}), If anb(R_iT_{less}) is activated (R_i□D, $i \neq 2$), it means R_i doesn't choose the T_{opt}. Then R_2 got the opportunity to choose T_{opt}. Therefore, anb(R_2T_{opt}) is stimulated by anb(R_iT_{less}). In Jerne's hypothesis, it means the paratope of anb(R_2T_{opt}) is recognized by the idiotope of anb(R_iT_{less}). And in our AIN model, the relation is stimulation INT+. In the same way, when anb(R_iT_{opt}) or anb(R_2T_{less}) is activated, anb(R_2T_{opt}) will be suppressed. And the relation between them is suppression INT-. From the above analysis, the interactions among the antibodies (INT) within a robot and from different robots have been clarified.

Based on the antigen stimulus and the stimulation/suppression among the antibodies, the concentration of the anb(R_iT_{opt})(R_i□D) is calculated by

$$da_i / dt = (\sum_j r_{ji}a_j - \sum_k r_{ik}a_k + g_i - k_i)a_i \tag{11}$$

Here a_i is the concentration of antibody i, the first term is the stimulation between antibody i and j. The second term is the suppression between antibodies. g_i is the antigen stimulus, and k_i is the natural extinction. To enlarge the overall capabilities of robots, the stimulation and suppression among antibodies is set to be proportional to robot's capability for task. Among all the anb($R_i T_{opt}$), R_i□D, the antibody with the highest concentration is activated for antigen T_{opt}, and correspondingly T_{opt} is allocated to R_i. If two antibodies have the same concentration, one is randomly chosen. If R_2 does not win T_{opt}, it goes back to step 1. It should be mentioned that for each robot can perform one task at a time, only one antibody within a robot is stimulated each time.

The allocation algorithm will be further analyzed and compared from the communication & computation aspects and will be verified in the simulations in Section 5.1.

3.2. The event-triggered dynamic allocation

For most conditions, a single allocation cannot complete all the tasks assigned. Therefore, reallocation arises.

Considering the load of communication, computation and response time into account, the following three events will trigger the re-assignment:

1) A new task appears;

2) A robot finishes the assigned task;

3) A robot arrives near the mission but cannot fulfill its task, requiring other robot's cooperation.

In the three cases, the original task assignment should be modified since the state of environment changed. The dynamic allocation is realized by the event-triggered reassignment based on the static allocation algorithm.

4. INTEGRATION OF THE AUTONOMOUS COOPERATION AND DYNAMIC TASK ALLOCATION

If the attributes of the tasks are unknown in advance, robots are required to cooperate autonomously during dynamic task allocation to increase the system efficiency. When robot finds it cannot finish the task independently, how to find desirable collaborators autonomously during dynamic task allocation is a problem. The integration of autonomous cooperation with dynamic allocation is described in this section.

4.1. Task allocation method for autonomously cooperative robots

Fig.3 shows the state transition diagram of the robots during the whole process. Initially, the robot stays in idle state. After being assigned the task, the robot goes into working state and begins to perform the task. Then it develops in two possibilities: 1) if the robot can accomplish the task independently (called simple task), it finishes the task and returns to idle state; 2) if the robot can not accomplish the task (called complicated task), it comes into waiting state, waiting for the cooperation from other robots. Autonomous cooperation is supposed to realize based on the dynamic task allocation. If all robots keep waiting for cooperation, the system turns to deadlock state. The ability to avoid and get rid of the deadlock state is required for adaptive system.

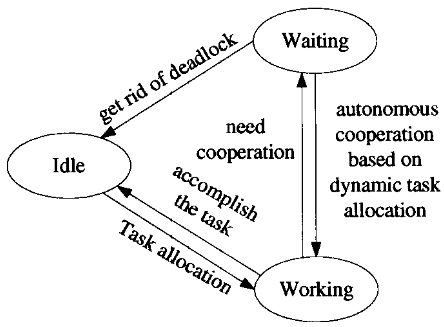

Figure.3 State transition of the robots

To realize the autonomous cooperation in multi-robot system, we focus on two points: 1) how to realize autonomous cooperation based on dynamic task allocation. 2) how to avoid and get rid of the deadlock state. In section 3, the interactions among the antibodies play an important role in task allocation algorithm. And in this section, we try to utilize the antigen stimulus to solve the above two points. We develop the dynamic task allocation method by integrating the cooperative idea into the antigen stimulus. And by the self-reinforcement learning of the antigen stimulus the autonomous cooperation among robots is realized and deadlock situation is avoided.

When some robot finds that it can't finish the task, it waits near the task for cooperation. To make the waiting robot return the working state and realize the autonomous cooperation, it should get the cooperation as soon as possible. The waiting robot is one source of the reinforcement signals, which is used to attract other robots to cooperate. And the antigen stimulus g_{ij} of R_i for the complicated task T_j get a positive reward r_a based on Equation (10)

$$\begin{aligned} g_{ij} &= g_{ij} + r_a \\ r_a &= w_1 \Sigma_{l=1}^{p_w} a_l \\ a_l &= f(v_l) \end{aligned} \tag{12}$$

where w_1 is the parameter and p_w is the number of the waiting robot near the task, and a_l indicates the ability of waiting robot R_l. In our paper, robots only differentiate in velocity, and f is an increasing function. Other factors can be considered for further research in function f. As r_a shown, the more waiting robots near T_j, the bigger reward gets. And the ability of the waiting robot has a positive effect on the reward.

Once some robot wait for cooperation near the task T_j, the antigen stimulus of other working robot R_i for T_j is positively rewarded. According to the allocation algorithm in Section 3, with the increase of g_{ij}, the probability of R_i to choose T_j is improved. And the waiting robots near T_j will get the autonomous cooperation and return to working state more quickly. As shown in Equation (12), more robots with bigger value of ability can get cooperation more quickly.

The second point is deadlock situation. Efficiently avoid and get rid of deadlock is required for adaptive system. A deadlock occurs when each robot is waiting near a specific task, but the number of waiting robots is not sufficient to perform the tasks. In this case, the robots keep waiting indefinitely and cannot complete the task. Therefore, the waiting time of robots is used as another source of the reinforcement signals.

Imitating the dissipation of the ant pheromone [15], the reinforcement signal produces passive reward r_p to avoid deadlock.

$$g_{ij}(t+1) = r_p(t_w) \times g_{ij}(t) \times q(O_j)$$
$$r_p(t_w) = \begin{cases} 1, & t_w \le t_0 \\ \eta, & t_w > t_0 \end{cases} \tag{13}$$

where g_{ij} is the antigen stimulus of R_i for T_j, t_w is the waiting time since R_i finds that it can't perform T_j. t_0 indicates threshold time of tolerance, which is a positive constant. $0 < \eta < 1$. O_j describes other factors about T_j, like the level of emergency or importance. $q(O_j)$ is the function of O_j.

The deadlock situation is avoided by introducing $r_p(t_w)$. When t_w>t0, the waiting robots still don't get enough cooperation to perform T_j, the antigen stimulus of R_i for T_j decreases. $g_{ij}(t+1) = \eta g_{ij}(t)$. Thus based on the task allocation algorithm, the probability of R_i to choose T_j is reduced, and R_i may choose other tasks with the decrease of g_{ij}. In this way, the deadlock is avoided.

By self-reinforcement learning of the antigen stimulus, two important points in autonomous cooperation in multi-robot systems are solved. As described in Section 3 and Section 4, an immune based dynamic task allocation method for autonomously cooperative robots has been proposed, which fully utilize the characters of the AIN system. The dynamic allocation method utilizes interactions among antibodies to allocate proper tasks to robots and adjusts antigen stimulus to realize the cooperation.

4.2. Three integration methods

As the attributes of the tasks are unknown, considering the limitation of the resource, we specify that one robot can only perform one task at certain time. According to the two variables of robot: committed/ opportunistic, individualistic/ coordinated [16], we propose several methods for autonomously cooperative robots based on the task allocation. For the first variant, being committed means that a robot cannot select other tasks before accomplishing its task. And being opportunistic implies the robot can render its current task and take a better suitable one during the task reassignment. Referring to the second variable, as AIN-model based system is fully autonomously distributed, each robot initially is individualistic and selects most suitable task independently. When there is a conflict after the primary task allocation, robots become coordinated and resolve the conflict cooperatively. Here three methods are proposed.

Method 1: The robot is opportunistic initially. Each robot calculates the capability to perform task based on Equation (10), and chooses applicable task according to the allocation algorithm in 3.1. When a robot reaches near a task and finds it impossible to finish the task independently, it will stay near the task, waiting for the cooperation. Here we call it a complicated task. In such situations, the system will be triggered to reassign tasks. The robots are still opportunistic during reassignment. For Method 1, the antigen stimulus of the complicated task keeps the same as the normal task, which means in Equation (12), w_1 is equals to 0.

Method 2 is mostly similar to Method 1 except for the antigen stimulus. To make it possible for the waiting robot to enter the working state, it should get the cooperation as quickly as possible. Method 2 uses the different antigen stimulus for the complicated tasks from the normal task. As shown in Equation (12), w_1 is not equals to 0.

Method 3 is identical to Method 1 in the early stage, using Equation (10) to calculate the antigen stimulus. The difference between them lies in that the waiting robot is allowed to select the most suitable robot to cooperate with the highest priority during the task reassignment. As shown in Equation (12), $w_1 \to \infty$. And the robot, which is selected by the waiting robot, turns its attribute from opportunistic to committed, while others remain opportunistic.

The three methods focus on different aspects and we will validate and compare their performances by the simulation experiments in Section 5.2.

5. SIMULATION AND DISCUSIION

5.1. Further analysis of allocation algorithm

Here we further analyze the immune base task allocation algorithm from the communication and computation aspects. And the result is shown in Table 1.

Communication and computation loads are important aspects for an allocation algorithm. It should be mentioned that to compare with other allocation algorithms with the same precondition, we assume the communication among the robots is perfect. Our allocation algorithm can totally work with local and imperfect communication.

Suppose n robots and m tasks. Each robot firstly selects the optimal task respectively. Then the robots communicate their optimal tasks to check whether there is conflict after separate selection. Here the communication load is $O(n)$. If there's a conflict, k robots are supposed to choose the same task ($k \leq n$). The k antibodies generated by k

robots share information to calculate the interactions and compare the concentration. In this part, the communication load is $O(2k)$. Therefore, communication overhead is $O(n+2k)$ per iteration.

Computation: Firstly every robot chooses the optimal task in parallel, and check whether the conflict is produced during the allocation. Here the computation load is $O(m+n)$ for each robot. When conflict is produced and k robots are supposed to choose the same task, the k corresponding antibody calculates the concentration. In this part, the computation load is $O(2k)$ for each robot. Thus computation overhead per iteration is $O(m+n+2k)$ for each robot.

Table 1 Communication and Computation Load

Algorithm	Computational Requirements / iteration	Communication Requirements / iteration
Immune based	O(m+n+k)	O(n+2k)
ALLIANCE [6]	O(mn)	O(m)
BLE [7]	O(mn)	O(mn)
M+ [17]	O(mn)	O(mn)

As classified by [4], our algorithm is simultaneous and reassignment, which are at least as good as those with sequential consideration and without reassignment.

5.2. Simulation

After the allocation algorithm is further analyzed, we then carry out simulations to verify the allocation algorithm and compare the three methods, which integrate the autonomous cooperation with dynamic task allocation. In our simulation, the task of the system is autonomous emergency handling. Alarms are produced in the field with various attributes, which are unknown ahead. Some alarms can be eliminated by single robot while others need the cooperation of more robots. The system is responsible for assigning alarm for each robot to eliminate, based on the location and capability of each robot. As indicated in [16], the simulation of emergency handling is a typical platform to measure the cooperation among robots. The most different point of our simulation is that the alarms' attributes are complicated and unknown, which add the complication and difficulty of the system.

The simulation environment is a $30*30m^2$ field with 30 alarms and 5 homogeneous robots which are all randomly located. Each alarm generate sound wave with certain frequency. After a robot detects the sound, it can determine the location and distance of the alarm. Robots can be heterogeneous. For the sake of convenience, here all the robots' speeds are set to $1m/s$. Once enough robots reach near the alarm, the alarm will be eliminated automatically. The performance index is the time it needed to clear all alarms (s), which is one of the most direct and typical benchmark of the efficiency of the robot system. The less time spent to finish the tasks, the better the performance is. We also account the deadlock times as a reference index.

As described in Section 3 and 4, the dynamic allocation method for cooperative robots is based on interactions among antibodies to realize task allocation and utilizes the self-learning of antigen stimulus to achieve autonomous cooperation. Therefore, the performance of the dynamic allocation method is analyzed from two aspects: 1) the performance of the immune based task allocation algorithm, where interactions among antibodies is fully utilized. 2) the performance of the dynamic allocation method by the learning of the antigen stimulus.

Most current allocation methods are based on greedy algorithm and result in degraded system performance [4]. In our immune based allocation algorithm, task allocation, which is not a greedy allocation algorithm, is executed not only by the antigen stimulus (different tasks), but also the interactions among antibodies (different robots). The system performance of the immune based task allocation algorithm is compared with the greedy allocation algorithm in the simulations. In the simulations, the tasks are all simple tasks, which only need one robot to finish. Table 2 lists the average performance of 100 simulations. The result shows the immune based task allocation algorithm has better working efficiency than the greedy one, which is commonly used.

Table 2 Simulation Result

Allocation Algorithm	Performance Index (s)
Immune based	60.14
Greedy	65.40

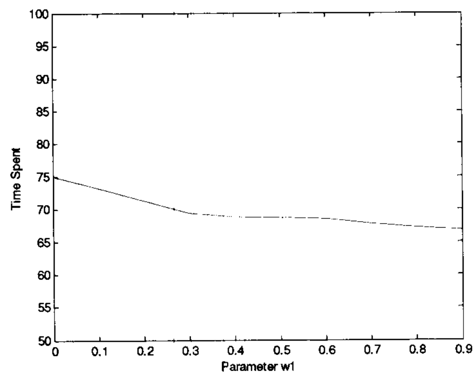

Figure 4. System performance impacted by parameter w_1 of Method 2

Based on the efficient allocation algorithm, the dynamic allocation method is proposed to realize autonomous cooperation among robots by integrating the self-learning antigen stimulus. To analyze the performance of the method, the difficulties of tasks in the simulation are complicated and unknown ahead. The average result of 100 simulations is shown in Fig.4. When w_l=0, no learning of antigen stimulus is pursued and no special consideration for autonomous cooperation. With the addition of w_l in Equation (12), the system increases the possibility of selecting complicated task for the robot by increasing the value of antigen stimulus, thus improving the probability of the cooperation with the waiting robots. From Fig.4, we find that the existence of w_l can improve the performance of the system greatly.

We then compare the three methods mentioned in Section 4. As illustrated above, it's not difficult to find that Method 1 is essentially a special case of Method 2 with w_l=0 and Method 3 with $w_l \to \infty$. In the simulation, we casually set w_l=0.6 in Method 2. Fig.5 shows the performance result. From Fig.5 we can conclude that three methods have verified to be able to finish all the tasks with autonomous cooperation and Method 2 is obviously better than Method 1 and 3 almost in every run. And the statistics in Table 3 show that Method 2 takes least average time. Therefore, we get conclusion that Method 2 has better working performance than Method 1 and 3. This conclusion accords with the result of the first set of simulations shown in Fig.4. The simulations all reveal that the existence of w_l (Method 2) improves the system performance, but the infinite large value of w_l (Method 3) doesn't show better performance.

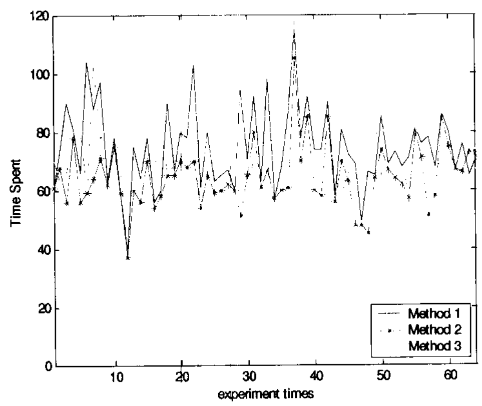

Figure 5. Performance of the three methods

Table 3. Simulation result of the three methods

Performance \ Method	1	2	3
Average time spent	74.5930	64.4375	71.7500

Here we further analyze the simulation result of Method 1, 2 and 3. First, compared with Method 1, Method 3 has the obvious advantage in the situations with relatively more tasks. For Method 3, giving the waiting robots the highest priority, they choose their coordinator firstly. As the cooperation is committed, the waiting robots can quit the waiting state and perform new task soon, Method 3 makes more fully use of the robots than Method 1. Therefore, Method 3 is more suitable for environments with relatively more tasks. Then, compared with Method 2, Method 3 cares about the waiting robots too much, meanwhile sacrificing the efficiency of the non-waiting robots. So the overall performance of the system is affected. Method 2 is the compromise of Method 1 and 3. It improves the probability of cooperation with the waiting robots by increasing the corresponding antigen stimulus, but never gives the waiting robots the highest priority, which guarantees the non-waiting robots' working efficiency. Therefore, the overall performance of Method 2 is the best.

Compared with [16], ours adds the complexity of the tasks and the attributes of the tasks are unknown. This paper also offers a good selection (Method 2) to make up the conclusion of [16], which claims that there is no single strategy with committed or opportunistic that produces best performance in all cases.

From the above stimulations and analysis, the dynamic task allocation method has been validated to realize autonomous cooperation based on the efficient task allocation algorithm. We also get the conclusion that proper value of parameter w_l in self-learning of antigen stimulus can improve the system performance greatly.

6. CONCLUSION AND FUTURE WORK

How to integrate the autonomous cooperation with dynamic task allocation in the multi-robot system is a big challenge for us. The robots are required to realize autonomous cooperation, as well as increase system's working efficiency.

This paper presented an AIN model for multi-robot system, which fully exploits the interactions both from inter- and intra-robot. The immune-based static allocation algorithm utilizes the interactions among the antibodies. And based on the allocation algorithm, the dynamic allocation method integrated the idea of autonomous cooperation into self-learning of stimulus antigen. And according to the attributes of the robot, three different methods are proposed to the integration of the autonomous cooperation and the dynamic task allocation, and these methods were validated and compared in the simulation. The simulation proved that the allocation method can realize the autonomous cooperation among robots and finish the task efficiently.

Several issues remain for future work. The task allocation algorithm we proposed is validated to have better allocation efficiency than the greedy allocation algorithm in simulations. However more formal proof should be given in our future research.

Another future work is to adjust the value of parameter w_l or generate adaptive w_l with the change of the environment to improve the working efficiency of multi-robot system. This method will be validated in real mobile robot platforms.

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