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Task Allocation Based on the Immune Network Adjusted by the Leukocyte in the Multi-Robot Systems

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Abstract: In order to solve the task allocation in the autonomous cooperation of the multi-robot systems, a novel artificial immune network allocation model adjusted by the leukocyte is presented in this study. Inspired by the Jerne's idiotypic immune network hypothesis, the stimulation between the antibody and antigen and the stimulation and suppression among different antibodies are defined firstly through regarding the B-cell, antibody and task as the robot, robot behavior and antigen, respectively. In order to further improve the allocation efficiency of the multi-robot systems, a novel immune network allocation model with the leukocyte adjustment is presented according to the biological mechanisms of the leukocyte. Moreover, the immune memory is introduced to improve the allocation efficiency and the dynamic adaptability of the artificial immune system. Compared with other immune algorithm, the simulation results in several environments show that the proposed allocation algorithm obviously improves the cooperation performance and reduces the consumption time, transport distance and energy waste of the task, which verifies the effectiveness of the proposed algorithm.

Key words: Multi-robot systems, immune network, task allocation, leukocyte

INTRODUCTION

As one of the key technologies in the multi-robot cooperation, the task allocation refers to allocating different sub-tasks of application tasks to different robots with the less resource consumption and the minimal task completion time (Mataric *et al*., 2003; Dong *et al*., 2007). At present, the task allocation methods of the multi-robot systems are usually divided into two categories, namely the conventional allocation algorithms and the artificial intelligence-based allocation algorithms. The former mainly includes the auction method (Wang *et al*., 2004; Nanjanath and Gini, 2006; Gurzoni *et al*., 2011), negotiation method (Wang *et al*., 2009) and game theory based-method (Wang *et al*., 2009) etc. Heap and Pagnucco (2011) proposed a sequential single-cluster auction method; however, it was difficult for the method to achieve the global optimal solution. Leon (2011) proposed a new negotiation method, which took its dynamics and concentration of greed into consideration; however, the role assignment of each robot was not clarified and the global optimization was still not solved. Li and Yang (2013) proposed a task distribution method based on the game theory, which took achieving the optimal task allocation and accelerating the task completion speed as the allocation target; however the method didn't apply to the task allocations in the unknown environments. The latter allocation methods are developed with the artificial intelligent and include ant colony algorithm (Xu *et al*., 2009; Wang *et al*., 2013), genetic algorithm (Zuo *et al*., 2011), artificial immune (Zhiwei *et al*., 2013) etc. Liu and Zhang (2010) presented a multi-robot task allocation based on a particle ant colony algorithm and the simulation results indicated that the task consumption time was small; however, the calculation amount was big. Huang and Gong (2006) provided a multi-robot task allocation method based on an improved Genetic Algorithm (GA) and solved the global optimization of the task allocation; however, the coding of the GA was complicated, the calculation was bigger and it was easy to trap into local minimum. Based on the Jerne's idiotypic immune network hypothesis, Gao and Wei (2006) provided an immune network task allocation method for the multi-robot in unknown environments.

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Wu *et al.* (2008) improved the allocation model by adding the T cell. The simulation results show that the immune network model could solve the task allocation of the multi-robot systems very well and the model was characterized by good robustness; however, the allocation efficiency was not very high. In this study, to further improve the task allocation performance of multi-robot systems, the level adjustment of the leukocyte and the immune memory are introduced into the immune allocation model. Large numbers of simulation results show that the proposed task allocation model solves the optimal allocation of the resources in the multi-robot systems and accelerates the task completion speed.

MATERIALS AND METHODS

Idiotypic immune network hypothesis: Biological immune system is a complicated system composed of many organs, molecules and cells. At present, the understanding to biological immune system by human beings is not very comprehensive. In 1973, according to the understanding to the idiotypic characteristic of antibodies in the modern immunology, Jerne (1973) proposed the famous idiotypic immune network hypothesis based on the Burnet's clonal selection theory. The hypothesis assumes that different types of antibodies and lymphocytes communicate with each other and maintain stable network equilibrium. The idea of the Jerne's hypothesis is schematically shown in Fig. 1. From the figure, it can be seen that the immune network is formed through interaction of the stimulation and suppression among B cells, antigen epitope, antibody idiotope and antibody paratope. Each antibody does not exist independently in the biological body, but is bound with other antibodies. The antigen epitope can not only be identified by other antibodies, but the antibody idiotope can also be identified by other antibodies.

Dynamics model of the idiotypic immune network: In order to successfully apply Jerne's idiotypic immune network hypothesis to the engineering, Farmer *et al.* (1986) firstly proposed the dynamics model Eq. 1 and 2 describing the stimulation level of the antibodies and the antibody concentration in the immune network hypothesis:

$$A_i(t) = A_i(t-1) + (\alpha * \frac{\sum_{j=1}^{N}(m_{ij}a_j(t))}{N} - \alpha \cdot \frac{\sum_{k=1}^{N}(m_{ij}a_k(t))}{N} + \beta g_i - k_i) \cdot a_i(t) \quad (1)$$

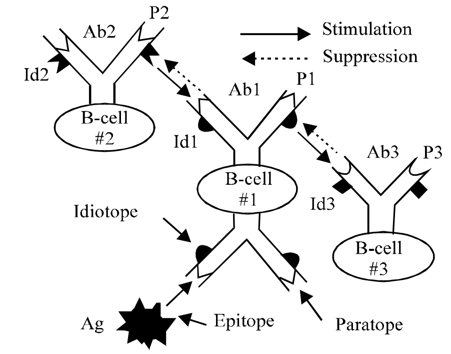

Fig. 1: Schematic structure of Jerne's idiotypic immune network

$$a_i(t) = \frac{1}{1 + \exp(0.5 - A_i(t))} \quad (2)$$

where, $A_i(t)$ is the stimulation value that the antigen and other antibodies which connect with antibody i (i = 0,……N-1) spread to the antibody i. The variable N is the total number of the antibodies in the immune network, $m_{ij}(t)$ is the mutual stimulation and suppression between the antibody i and antibody j(j = 0,……N-1) and $a_i(t)$ is the concentration of the antibody i. The two other variables, namely α and β, are the constants.

In Eq. 1, the first term on the right hand side represents the stimulation between the antibody i and j. The second term represents the suppression between the antibody i and j. The third term represents the stimulation from the antigen. The fourth represents the natural death.

Since, the dynamics model of the idiotypic immune network hypothesis is put forward, it has been widely paid attentions to and successfully used in the robotics, such as dog and sheep problem in the distributed autonomous robotics system (Meshref and Vanlandingham, 2000) and the garbage-collecting problem (Ishiguro *et al.*, 1996).

Task allocation model based on the idiotypic immune network: In order to solve the robot task allocation, the pushing-box problem in the multi-robot systems is taken as an example. Regarding the B-cell and the box as the antibody and the antigen, respectively, the mutual action among the mobile robots and the boxes is used to simulate the idiotypic immune network hypothesis firstly; then, the robots are selected to finish the task allocation of the boxes according to the antibody concentration which is calculated based on the Farmer's dynamics model. The corresponding relationship between the biological immune system and the artificial immune allocation system is shown in Table 1.

Table 1: Corresponding relationship between the biological immune system and the artificial immunity allocation system

Biological immune system	Artificial immune allocation system
Antigen	Task
B-cell	Robot
Antibody	Robot behavior
Antigenic determinant	Information of the box
Stimulation of the antigen	Action from the box to the robot
Stimulation among the antibodies	Attraction among the robots
Suppression among the antibodies	Repulsion among the robots

In the immune task allocation model based on the immune idiotypic network hypothesis, the robot has four behaviors, namely leisure, moving to the box after being stimulated, waiting and pushing the box to the goal. At the beginning, the allocation system finishes the initial allocation according to the distance between the antibody and the antigen. After the robot moves to the box, if it can push the box independently, it completes the task; otherwise, it stimulates other robots to come to cooperation until all the tasks are finished.

BASIC DEFINITIONS OF THE IMMUNE ALLOCATION MODEL

Affinity between the antigen and the antibody: In the pushing-box problem of the multi-robot systems, the task allocation is finished through selecting the appropriate robots according to the affinity between the antigen and the antibody. In order to accelerate the response of the mobile robots to the task, the moving speed of the robot and the distance between the robot and the box are taken as the variables and the affinity between the antigen and the antibody is defined as follows:

$$g_i^k = 1 - \delta \cdot \frac{d_{ik}}{v}, i, k = 1,2,...., N \tag{3}$$

where, d_{ik} is the distance between the robot i and the box k, v_i is the moving speed of the robot i and δ is the regulation coefficient. In this study, δ is 0.01. From Eq. 3, it can be seen that when the distance between the robot i and the box k is smaller and the moving speed v_i of the robot i is higher, the value of the affinity g_i^k between the antigen and antibody is larger, that is to say, the possibility that the robot i is selected is bigger, which accelerates the response of the mobile robots to the task in a short time.

Stimulation and suppression coefficients among the antibodies: If robot i which is selected by the Eq. 3 cannot complete the task k alone, it will initiatively stimulate other idle robots which are close to the task k to cooperate to finish the task. In order to improve the stimulation effect among different antibodies, besides considering the positions and the ability of different robots, the immune memory is introduced to further to strengthen the self-learning of the stimulation and suppression among different antibodies. Let m_{ij} be the stimulation of a waiting robot i to idle robot j, it can be defined as follows:

$$m_{ij} = m'_{ij} + r.g_j^k \tag{4}$$

$$m'_{ij} = \eta.\frac{f_i}{f_j} + \mu.\frac{1}{d_{jk}}, \quad i, j=1...N; k=1...m \tag{5}$$

where, r is the learning rate and r = 0.4. The weight values η and μ are 0.7 and 0.3, respectively. The variables f_i and f_j are the capability of the robot i and the robot j, respectively and d_{jk} is the distance between the robot j and the box k. In Eq. 4 and 5, the capability ratio of the robot i and j, the distance between the robot j and the box k and the affinity between the antigen and antibody are considered in the calculation of the stimulation and suppression among different antibodies. Therefore, the robot which has stronger capability than the robot i and is more close to the box k is selected with higher probability. The introduction of the self-learning of the antibody increases the stimulation value among different antibodies, which is benefit to accelerate the response speed to the task and improve the allocation effect.

Immune adjustment based on the level of the leukocyte: The leukocyte in the biological immune system has the capability of devouring the foreign materials and producing the antibodies. In the biological immunology, after leukocyte devours the antigens, its antigenic determinants are delivered to the lymph cells and then the specificity immune response of the lymph cell is induced. Considering the biological immune capability of the leukocyte, the immune network adjustment function B_i based on the leukocyte is put forward to further improve the immune allocation efficiency in the multi-robot cooperation. The regulation function is defined as follows:

$$B_i = f_i \cdot v_i \left(\frac{1}{d_{ij}}.\cos^2\theta_{ikg} + \frac{1}{d_{kg}}.\cos^2\theta_{kgi} \right) \tag{6}$$

where, the definitions of f_i, v_i and d_{ij} are similar to the above definitions. The item $f_i.v_i$ denotes the robot power. The variable d_{kg} is the distance between the box k and the target point g, θ_{ikg} is the included angle of the line from the robot to the box and the line from the robot to the target point g and θ_{kgi} is the included angle of the line from the box to the target point and the line from the target point to the robot. In order to reduce the energy waste and task completion time during the pushing boxes, the robot capability, robot speed, distance from the robot to the box, distance from the box to the target point g and the included angle between the robot-box and the robot-target are considered. The robot power is projected to the line from the robot to the target point and the line from the box to the target to achieve the available power and the power is regarded as the adjustment function, which helps to decrease the energy waste and improve the system cooperation efficiency to the robots.

IMPROVED DYNAMICS EQUATION OF THE ANTIBODY CONCENTRATION

Based on the stimulation from the antigen to the antibody, the stimulation among different antibodies and the immune adjustment of the leukocyte, the new antibody stimulation value and antibody concentration are redefined in this study on the basis of the Farmer's dynamics model:

$$A_i^k(t) = A_i^k(t-1) + \left(\alpha \sum_{j=1}^{n} m_{ij} \cdot a_j^k(t-1)/n + \beta \cdot g_i^k - B_i - k_i\right) \cdot a_i^k(t-1) \tag{7}$$

$$a_i^k(t) = \frac{1}{1+\exp\left(0.5 - A_i^k(t)\right)} \tag{8}$$

where, i, j = 1,.....,n; k = 1,...., m. The two variables α, β are the interaction ratio of the antibody i to other antibodies and antigen, respectively and k_i is the natural mortality of the antibody i.

FLOW OF THE IMMUNE NETWORK TASK ALLOCATION ALGORITHM FOR THE MULTI-ROBOT SYSTEMS

- **Step 1:** Initialize algorithm parameters and the states of the robots and tasks
- **Step 2:** Calculate the affinity of each task (antigen) and the robot (antibody) according to the Eq. 1
- **Step 3:** Allocated the robot with the maximum affinity to the task
- **Step 4:** Judge whether the robot can finish the task after it reaches the task. If can, then it push the box to the goal alone and turn to Step 6; otherwise, turn to Step 5
- **Step 5:** Calculate the stimulation coefficient between the waiting robots and idle robots according to the Eq. 4 and 5 firstly; then calculate the adjustment function B_i according to the Eq. 6; finally, calculate the concentration values of all robots according to Eq. 7 and 8 and allocate the robot with the maximum concentration to cooperatively push the box and turn to Step 4
- **Step 6:** Judge whether all the tasks are finished. If done, then end; otherwise, turn to Step 2

RESULTS AND ANALYSIS OF THE TASK ALLOCATION FOR THE MULTIPLE ROBOTS

Allocation environments: In order to verify the effectiveness of the proposed leukocyte adjustment-based immune network algorithm (LAINA), the simulations of the task allocation in eight environments are implemented on an Intel Pentium IV 2.53 GHz computer with 2GB RAM using the MATLAB language. The testing results of the LAINA are compared with the Immune Network Exploration Algorithm (INEA) Wu *et al*. (2008). The parameters of the eight environments are shown in Table 2. In each environment, the coordinates of the robots and boxes are not the same. The main parameters of the proposed allocation algorithms are set as follows: $\alpha = 0.5$, $\beta = 0.1$, $k = 0.002$, $A_i^k(0) = 0.5$, $a_i^k(0) = 0.5$.

Results and analysis of the task allocation: Table 3 gives the comparisons of the allocation results among two immune allocation models in eight different environments. From the table, it can be seen that the INEA and LAINA

Table 2: Parameters for the task allocation of multi-robot systems in eight environments

Parameters	Pushing ability of the robots (kg)	No. of the robots	Mass of the boxes (kg)	No. of the boxes
1	2, 2, 2, 3, 5	5	2, 4, 5, 10	4
2	2, 2, 3, 3, 4	5	2, 4, 4, 8	4
3	1, 2, 2, 3, 5	5	2, 4, 5, 10	4
4	2, 2, 2, 4, 6	5	2, 4, 8, 12	4
5	2, 3, 3, 4, 5	5	2, 3, 10, 13	4
6	2, 2, 3, 3, 5	5	2, 4, 5, 10, 8	5
7	2, 2, 3, 3, 5	5	2, 4, 5, 6, 10	5
8	2, 2, 3, 2, 4, 2	6	2, 4, 6, 8	4

Table 3: Comparisons of task allocation results between INEA and LAINA in eight environments

	Gross time of task completion (s)		Energy waste (kg)		Gross length of transport path (m)	
Environments	INEA	LAINA	INEA	LAINA	INEA	LAINA
1	230	220	4	1	164.0	150.0
2	157	148	5	2	83.3	74.6
3	216	200	4	1	154.9	128.9
4	159	114	8	2	109.7	90.4
5	187	185	6	1	133.8	124.9
6	144	130	7	4	103.5	99.1
7	192	168	14	6	111.1	104.1
8	163	161	9	4	103.3	102.8

INEA: Immune network exploration algorithm, LAINA: Leukocyte adjustment-based immune network algorithm

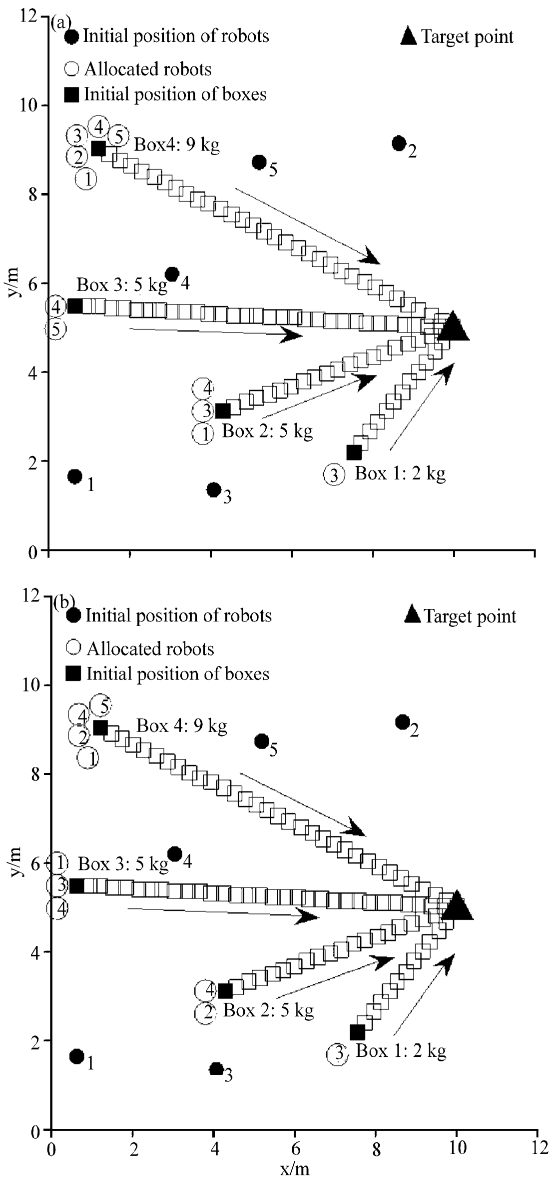

Fig. 2(a-b): Allocation results of two immune allocation algorithms in environment 3, (a) Allocation result based on INEA and (b) Allocation result based on LAINA. INEA: Immune network exploration algorithm, LAINA: Leukocyte adjustment-based immune network algorithm. Symbols ①, ②, ③, ④ and ⑤ represent Robot 1, 2, 3, 4 and 5, respectively

all can make the best of the immune performance of the recognization, learning and memory to solve the task allocation in different environments. From the gross time of task completion, energy waste and gross length of transport path, it can be seen that there are obvious differences among two models. Although, the T cell is added in the immune network in the INEA, the action of the T cell is not obvious during the task allocation. Because the more reasonable affinity between the antigen and the antibody is redefined through considering the robot ability, the robot speed and the distance synthetically in the proposed LAINA and the immune learning and the immune adjustment of the leukocyte are introduced, the gross time of task completion and the energy waste are decreased and the gross length of transport path is shortened. From the Table 3, it can be seen that the allocation results of the proposed LAINA is the best.

Compared with the auction method, such as the sequential single-cluster auction method (Heap and Pagnucco, 2011), the proposed LAINA is characterized by global allocation ability and the allocation accuracy is improved. Compared with the negotiation method proposed by Leon (2011), the immune allocation mechanism of proposed LAINA based the stimulation and suppression among different antigens and antibodies improves the allocation speed and the allocation efficiency is improved. Compared with the game theory based-method proposed by Wang *et al.* (2009), the proposed LAINA can solve the task allocation in unknown environments. In addition, although the allocation method based on genetic algorithm (Huang and Gong, 2006) solved the problem of global optimization, the calculation of genetic algorithm was bigger and was not suitable for the multi-robot system which high real-time property. The allocation model of proposed LAINA based on Farmer's dynamics model is simple and the calculation is smaller. So, the LAINA is more suitable for the task allocation of multi-robot system than the genetic algorithm. From the above comparisons among different allocation methods, it can be seen that the allocation performance of the proposed LAINA is the best and it is more suitable for the multi-robot system in this study.

In order to further analyze the robot task allocation based on the immune network, the cooperation of two immune allocation algorithms in environment 3 is shown in Fig. 2.

From Fig. 2, it can be seen that the different boxes are allocated to the different robots by the different allocation strategies in the same environments. Taking the allocation result of the proposed LAINA as an example, it can be seen that the box 1 is moved by robot 3; the box 2 is moved by the robots 2 and 4; the box 3 is moved by robots 1, 3 and 5 and the box 4 is moved by robots 1, 2, 4 and 5.

Figure 3 and 4 give the moving trajectories of all robots for INEA and LAINA in Environment 3. From the

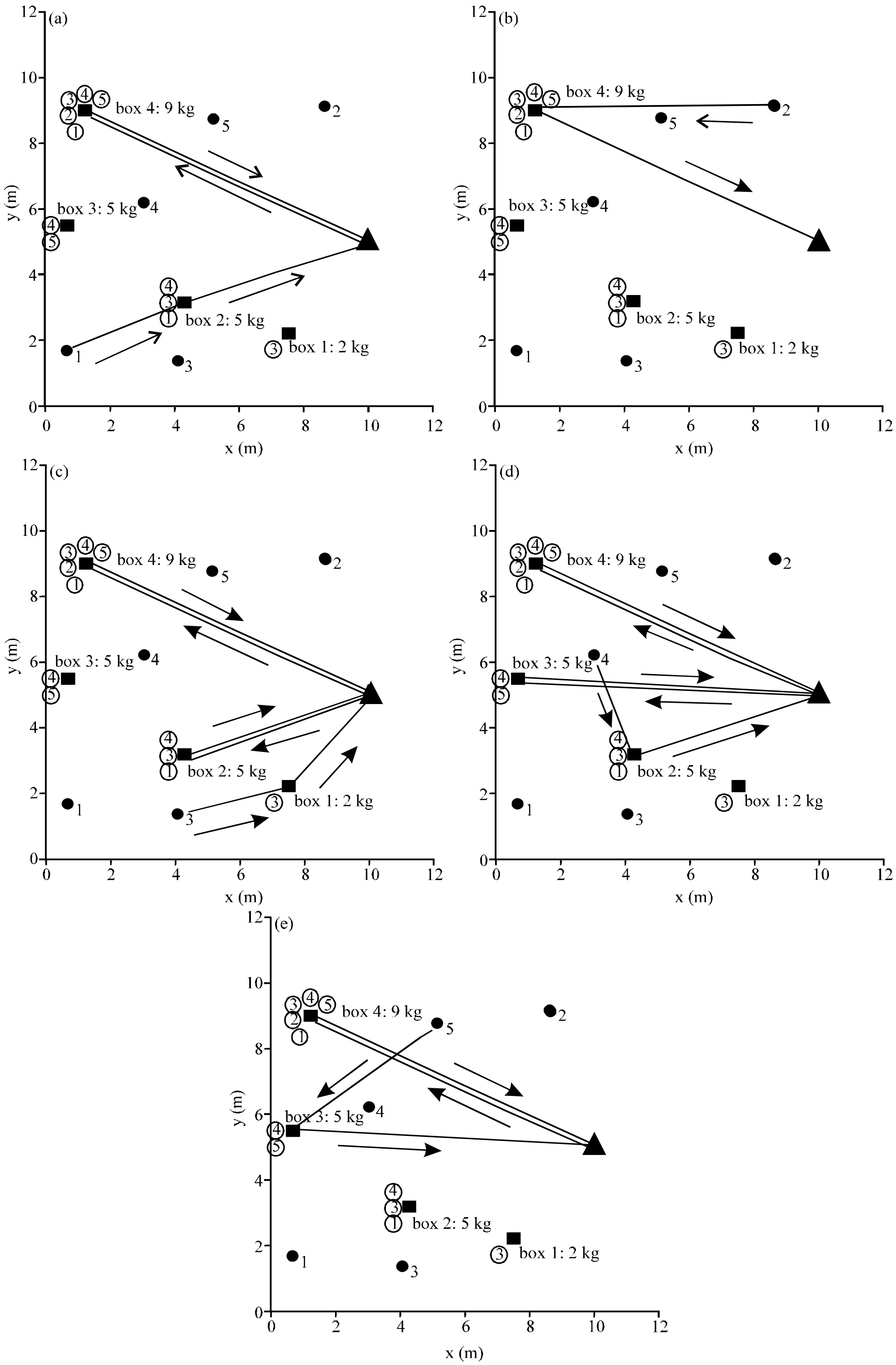

Fig. 3(a-e): Moving trajectories of five robots for the INEA in environment 3, (a) Moving trajectory of robot 1, (b) Moving trajectory of robot 2, (c) Moving trajectory of robot 3, (d) Moving trajectory of robot 4 and (e) Moving trajectory of robot 5. INEA: Immune network exploration algorithm. Symbols ①, ②, ③, ④ and ⑤ represent robot 1, 2, 3, 4 and 5, respectively

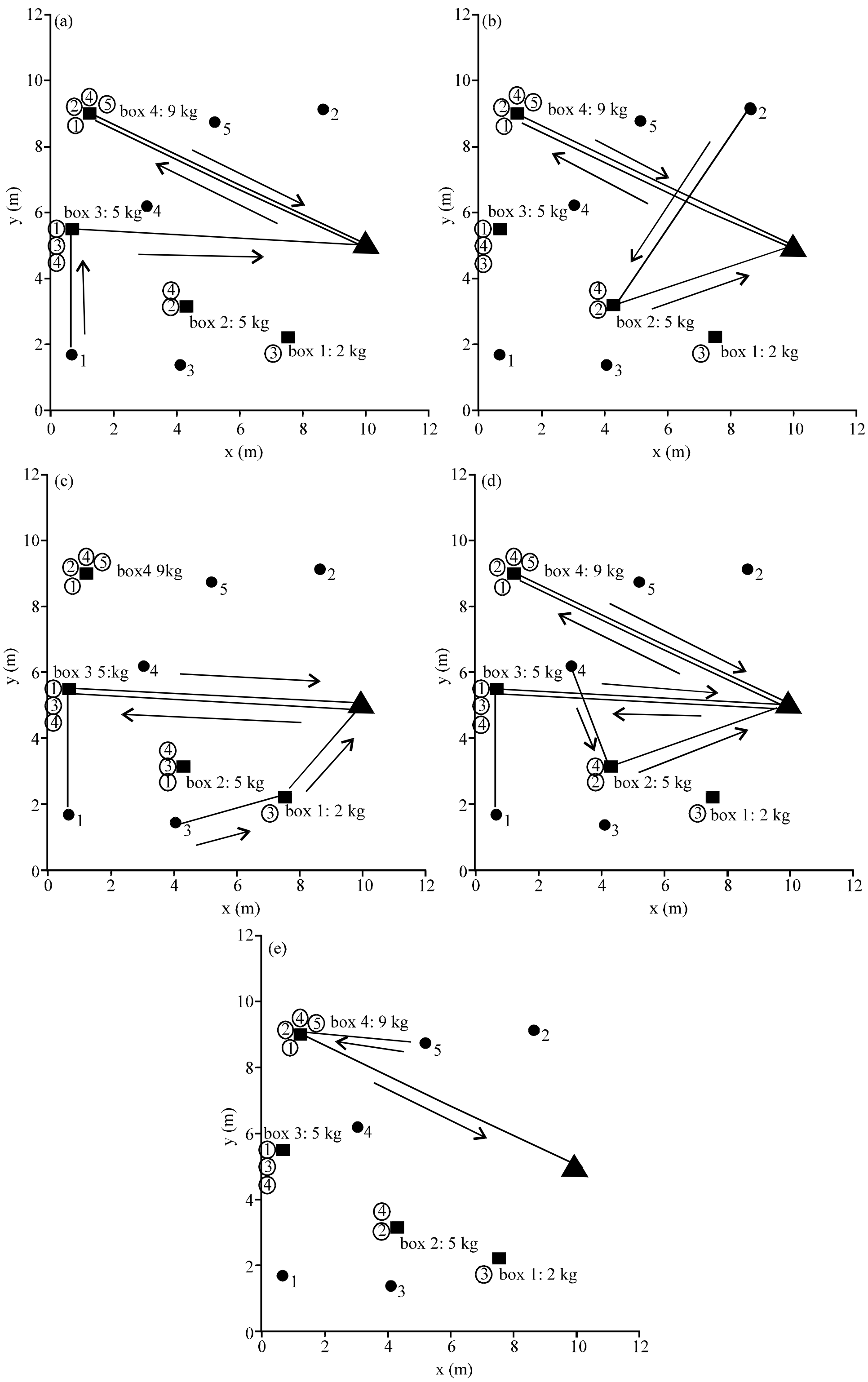

Fig. 4(a-e): Moving trajectories of five robots for the LAINA in environment 3, (a) Moving trajectory of robot 1, (b) Moving trajectory of robot 2, (c) Moving trajectory of robot 3, (d) Moving trajectory of robot 4 and (e) Moving trajectory of robot 5. LAINA: Leukocyte adjustment-based immune network algorithm. Symbols ①, ②, ③, ④ and ⑤ represent robot 1, 2, 3, 4 and 5, respectively

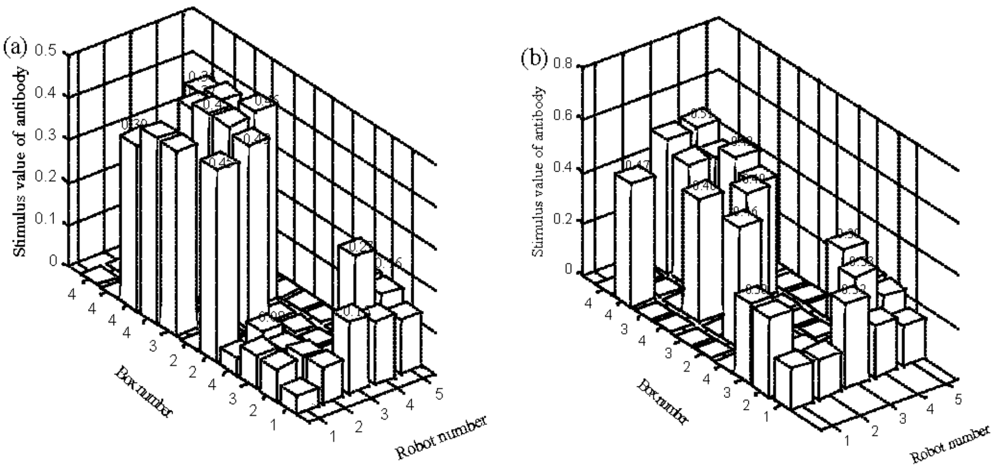

Fig. 5(a-b): Stimulation value of two immune allocation algorithms in environment 3, (a) Stimulation value of INEA and (b) Stimulation value of LAINA. INEA: Immune network exploration algorithm, LAINA: Leukocyte adjustment-based immune network algorithm

figure, a conclusion can be drawn that the tasks which are allocated to the robots by the different allocation strategies are different. Taking the moving trajectory of robot 3 for INEA as an example, it can be seen that the robot 3 firstly moves the box 1 to the goal alone, then it moves the box 2 with the robots 1 and 4 to the goal; finally, it moves the box 4 with the robots 1, 2, 4 and 5 to the goal. However, in the proposed LAINA, the robot 3 firstly moves the box 1 to the goal alone and then it moves the box 3 only with the robots 1 and 4 to the goal.

Figure 5 gives the stimulation value of two immune allocation algorithms in Environment 3.

From the figure, it can be seen clearly how the robots are selected by calculating the antibody stimulation value and which robots are selected to complete the tasks through the mutual cooperation. Taking the proposed LAINA as an example, it can be seen that the box 1 is moved by the robot 3 and the antibody stimulation value of is 0.30. The box 2 is allocated to the robot 4; however, the robot can't push it independently. So, the immune allocation system carries out the second task allocation and selects the robot 2 from the idle robots to push the box 2 together. The box 3 selects the robot 1 in the fist allocation; however, it still can't push the box 3 alone, so the robot 5 is selected by the immune allocation system from the idle robots to push the box 3 with the robot 1. Because the box 3 is so heavy that the two robots still can't push it. Finally, the robot 3 is selected again to push the box 3 together. As for the box 4, it is so heavy that four allocations are carried out, that is to say, the robots 1, 2, 4 and 5 are chosen to push the box 4 successfully. Figure 5 further shows how the robots are selected by calculating the antibody stimulation value, which indicates the dynamic balance of the immune network allocation system in this study. Fig. 5a also gives the task allocation by the selection of antibody stimulation value in the INEA.

CONCLUSION

In order to solve the multi-robot task allocation, a new immune network model (namely LAINA) has been put forward on the basis of the existing immune network model. Through a large number of simulations, the following conclusions can be drawn:

- Taking the B-cell, antibody and task as the robot, robot behavior and antigen, respectively, on the basis of the Jerne's immune idiotypic network hypothesis, the redefinitions regarding the stimulation between the antibody and antigen and the stimulation and suppression among different antibodies further make the task allocation be more reasonable
- The immune memory is introduced into the immune network allocation model and it further strengthens the self-learning of the stimulation and suppression among different antibodies
- Inspired by the biological immune capability of the leukocyte, the adjustment of the leukocyte is introduced into the immune network allocation model and the immune adjustment function is defined, which further improves the allocation efficiency
- The simulation results show that the proposed LAINA obviously improves the cooperation performance and reduces the consumption time, task transport distance and energy waste of the task

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