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A Novel Mutual-coupled Immune Network Algorithm with the Characteristic of Memory for Mobile Robot Path Planning

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Abstract: To solve the path planning of mobile robots in complex environments, on the basis of Jerne's idiotypic immune network hypothesis, a novel memory-based Mutual-coupled Immune Network Planning Algorithm (MMCINPA) is proposed. First, according to the obstacle and goal information surrounding the mobile robot, two environment-oriented and goal-oriented immune networks are defined to construct the mutual-coupled immune network for the robot path planning. Then, taking the obstacle and goal as antigen and taking the robot behavior as antibody, the path planning of mobile robot in complicated environments is realized through the antibody selection under the stimulation and suppression among antigen and antibodies. To further improve the planning efficiency of artificial immune network, the historical selected antibody is taken as the immune memory cell and its frequency of usage is added in the calculation of antibody concentration. Compared with Ishiguro's Simple Mutual-coupled Immune Network Planning Algorithm (SMCINPA), the simulation results in four static environments show that the length of path planned by proposed MMCINPA shortens by about 5.97% and the average turning angle of path by MMCINPA decreases by about 30.11%, which shows the strong planning ability and good flexility of MMCINPA. The path planning result in dynamic environment also verifies the robustness of MMCINPA in uncertain environment.

Key words: Mobile robot, path planning, mutual-coupled immune network, immune memory cell

INTRODUCTION

Path planning is one of the key technologies in autonomous navigation of mobile robot. The aim of path planning is to find an optimal collision-free path from the starting point to goal based on certain optimization criterion, such as, minimal working cost, shortest walking route (Yuan *et al*., 2010a). At present, the common path planning methods include Artificial Potential Field (APF) method (Ge and Cui, 2002), fuzzy logical method (Wang *et al*., 2012), Ant Colony Algorithm (ACA) (Zhao and Li, 2010), Genetic Algorithm (GA) (Yuan *et al*., 2012) and so on. The APF method is characterized by simple model, small calculation and good real time; however, it is easy to trap into local minima and swing in narrow channel. The fuzzy logical method owns strong robustness and overcomes the local minima in complicated environments; however, its computation amount will become larger and larger with the increase of the number of obstacles, which will affect the planning performance. The ACA has the distributed global search ability; however, its planning results are limited to the divisions of a grid because its environmental modeling is mainly based on the grid method. The GA also has a global search capability, but its encoding is complicated and the search efficiency is low.

In recent years, the artificial immune algorithms based on the biological immune mechanism have been gradually applied to the field of robotics (Song, 2012, 2013; Tan *et al*., 2012), especially to the path planning in mobile robot navigation. Lu *et al*. (2012) presented a global path planning method including negative selection, clonal selection and immune vaccine. In the method, the antibody concentration is introduced into the construction of affinity to prevent the local convergence and improve the search efficiency. Yuan *et al*. (2010b) put forward a Hybrid ant Colony and Immune Network Algorithm (HCINA) based on improved APF. The path planning results of APF are taken as the prior knowledge and the network is initialized by the vaccine extraction and inoculation, which further improves the convergence speed of HCINA and shortens the length of planned path. Das *et al*. (2012) presented an Artificial Immune Algorithm (AIA) focusing on avoiding obstacles based on immune principle. The path planning results of AIA show that the mobile robot can avoid the obstacles, escape the local

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traps and reach the goal efficiently. Ishiguro *et al.* (1995) proposed a mutual-coupled immune network algorithm for mobile robot path planning based on the idiotypic immune network hypothesis and the planning results verify its validity; however, the antibodies in the planning algorithm was so simple that the planning performance needed to be further improved. This paper extends the original work presented by Ishiguro *et al.* (1995). The antibodies are redefined according to the detection distance of the sensors arranged around the robot and the historical selected antibody is taken as the immune memory cell to further optimize the immune network planning model. The simulation results of path planning in static and dynamic environments verify the effectiveness of the proposed Memory-based Mutual-coupled Immune Network Planning Algorithm (MMCINPA).

PLANNING MODEL BASED ON MUTUAL-COUPLED IMMUNE NETWORK

Idiotypic immune network hypothesis: The Biological Immune System (BIS) is a kind of self-defensive system that can prevent the invading of outside pathogen and clear invading pathogens and other harmful substances. The BIS is characterized by immune recognition, immune memory, immune learning and so on. Idiotypic network hypothesis (Jerne, 1973, Jerne and Cocteau, 1984), developed by Jerne based on the theory of clone selection in 1973 is one of the important immune theories and it can be schematically shown in Fig. 1 (Yuan *et al.* 2009). When the external specific antigen (Ag) substances invade the organism, the epitope, also known as antigenic determinant, will be recognized by the paratope of B-cell #1 and will stimulate B-cell #1 to produce large numbers of antibodies to eliminate antigen substances. Similarly, the antibodies produced and differentiated by B-cell #1 play the role of antigens to B-cell #2 and B-cell #3. Idiotope 1 (Id1) as the epitope of antigen acts on B-cell #3 and B-cell #3 will produce antibodies to suppress the antibody production of B-cell #1. By analogy, the stimulation and suppression among B-cells can effectively clear the antigen substances that invade the body to maintain the balance and stability of organism.

Mutual-coupled network model for path planning: To solve the robot path planning in complicated environments, an artificial immune planning model based on Jerne's idiotypic immune network hypothesis is designed. In this model, the environmental information regarding obstacles and goal are taken as the antigen and the immune agent, namely an omni-directional mobile robot (Fig. 2) is taken as the B cell.

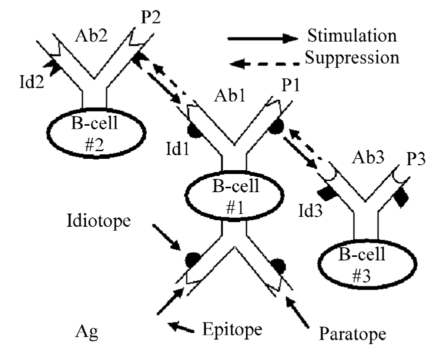

Fig. 1: Idiotypic immune network

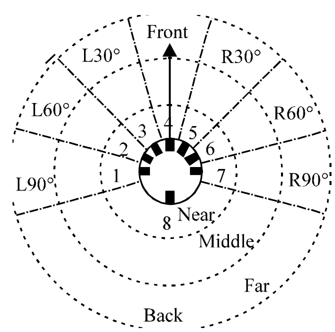

Fig. 2: Structure of omni-directional mobile robot (immune agent)

The robot is equipped symmetrically but unevenly with eight sensors around it. According to the importance of environmental information during the obstacle avoidance, seven sensors are arranged with the angle of 30° in front of the robot and one sensor is arranged at the back of the robot. The detection direction is 1~8 and the detection distance of each sensor is divided into three degrees: far, middle and near. The antibodies produced by B cells are the robot behaviors for the environmental information. In the planning system, the robot can move according to eight different moving instructions {a, b, c, d, e, f, g, h}, i.e. {turn left 90°, turn left 60°, turn left 30°, move forward, turn right 30°, turn right 60°, turn right 90° and move backward}. When the goal is located in the certain detection distance of one sensor, the robot stops moving and the planning task is finished.

Due to the complexity and uncertainty of the environment surrounding the robot, it's hard for robot to deal with the environmental information effectively using single immune network. In order to better solve the balance between the environmental elements and goal elements, on the basis of the immune network model developed by Ishiguro for mobile robot, a mutual-coupled immune network including environment-oriented immune network and goal-oriented immune network is used as shown in Fig. 3. In the environment-oriented network, the environmental information (namely the distance between obstacle and robot and the direction of obstacle relative to robot) detected by immune agent is taken as the obstacle antigen. In the goal-oriented immune network, the goal information (namely the direction of goal relative to robot and the status that the robot reaches the goal or not) is taken as the goal antigen. The principle of mutual-coupled immune networks for mobile robot path planning can be described: The robot (namely immune agent) will choose the optimal behavior (namely antibody with higher concentration) to avoid obstacles and approach goal under the stimulation of antigens (namely obstacles and goal) and the stimulation and suppression among antibodies in the immune network. The calculation of antibody concentration is based on Farmer's dynamics model (Farmer *et al*., 1986).

PATH PLANNING ALGORITHM BASED ON MUTUAL-COUPLED IMMUNE NETWORK

Definition of the antibody: The antibody represents the robot behavior that deals with the environmental information. From the designed planning model based on mutual-coupled immune network, we can see that there are two main types of antibodies: environment-oriented antibody and goal-oriented antibody. The former consists of precondition of obstacles avoidance (namely antibody

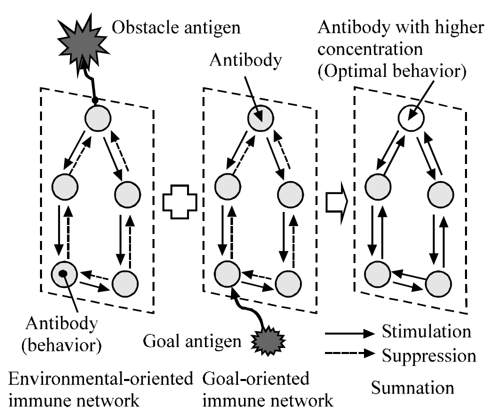

Fig. 3: Structure of artificial mutual-coupled immune network for mobile robot path planning

paratope) and robot behavior; the latter consists of precondition of goal approach (namely antibody paratope) and robot behavior. The detection distance of robot sensors (namely far, middle and near) is coded by binary string {01, 10 and 11}. If the obstacles are out of sensors, the detection distance is coded by 00. The encoding definition of antibody paratope is shown in Fig. 4.

In order to further improve the flexibility and robustness of the immune network and strengthen its planning ability, 22 groups of antibodies are defined in this paper. Figure 5 and 6 give the encoding definitions of antibodies in environment-oriented network and in goal-oriented network, respectively. In the two figures, symbol ## denotes that the condition is not very important and # can be taken as either 0 or 1.

Taking antibody 3 in Fig. 5 and 6 as an example, it can be seen that the antibody is a behavior of moving forward. In the environment-oriented network, the paratope of antibody 3 requires that there are no obstacles at left 60° and right 30° of robot, the obstacles are in the far detection range at left 30° and right 60°, the obstacles in front of robot are in the middle detection range and the obstacles at left 90°, right 90° and back of robot are dispensable. In addition, the goal can be located in any direction and the robot can approach or not approach the goal. In the goal-oriented environment, the paratope of antibody 3 requires that the obstacles can be located in any direction of the robot except right ahead, the goal is straight ahead of the robot and the robot doesn't approach the goal. It is no very important whether there are obstacles in other directions.

The path planning based on mutual-coupled immune networks is realized through the antibody selection according to the antibody concentration under the stimulation and suppression among antigens and antibodies. The antigen regarding obstacles and goal can be achieved by using the robot sensors.

Antibody selection: In the proposed planning model based on mutual-coupled immune network, the antibody selection depends on the amount of antibody concentration. The antibody concentration in immune network is often calculated according to Farmer's dynamic model. Because the planning network are divided into

<table>
<tr><th>L90°</th><th>L60°</th><th>L30°</th><th>Front</th><th>R30°</th><th>R60°</th><th>R90°</th><th>Back</th><th rowspan="2">Goal direction (1-8 or #)</th><th rowspan="2">Approach goal: 1
Otherwise: 0 or #</th></tr>
<tr><td colspan="8">Obstacle exists: 01 (Far), 10 (Middle) or 11 (Near)
Otherwise: 00 (None)</td></tr>
</table>

Fig. 4: Encoding definition of antibody paratope

No. of Antibody	Precondition of obstacles avoidance (Paratope)										Behavior
Antibody 1	##	##	##	00	##	##	##	##	#	#	Move forward
Antibody 2	00	##	00	01	00	##	##	##	#	#	Move forward
Antibody 3	##	00	01	10	00	01	##	##	#	#	Move forward
Antibody 4	##	##	##	##	##	##	##	00	#	#	Move back
Antibody 5	##	##	##	11	00	##	##	##	#	#	Turn right 30°
Antibody 6	##	##	##	10	01	10	##	##	#	#	Turn right 30°
Antibody 7	##	##	01	01	10	00	##	##	#	#	Turn right 30°
Antibody 8	##	##	11	11	11	00	##	##	#	#	Turn right 60°
Antibody 9	##	##	10	01	01	10	##	##	#	#	Turn right 60°
Antibody 10	##	##	11	##	00	10	01	##	#	#	Turn right 60°
Antibody 11	##	11	11	11	11	11	00	##	#	#	Turn right 90°
Antibody 12	##	10	00	##	11	10	01	##	#	#	Turn right 90°
Antibody 13	##	11	##	01	00	01	10	00	#	#	Turn right 90°
Antibody 14	##	##	00	11	##	##	##	##	#	#	Turn left 30°
Antibody 15	##	10	01	11	##	##	##	##	#	#	Turn left 30°
Antibody 16	10	01	10	01	##	##	10	##	#	#	Turn left 30°
Antibody 17	##	00	11	11	11	##	##	##	#	#	Turn left 60°
Antibody 18	##	01	01	10	11	##	10	##	#	#	Turn left 60°
Antibody 19	00	10	01	##	##	01	##	##	#	#	Turn left 60°
Antibody 20	00	11	11	11	11	11	##	##	#	#	Turn left 90°
Antibody 21	01	11	11	11	11	10	##	##	#	#	Turn left 90°
Antibody 22	10	00	01	##	##	##	##	00	#	#	Turn left 90°

Fig. 5: Encoding definition of antibody in environment-oriented network

No. of Antibody	Precondition of obstacles avoidance (Paratope)										Behavior
Antibody 1	##	##	##	00	##	##	##	##	4	1	Move forward
Antibody 2	##	##	##	01	##	##	##	##	4	1	Move forward
Antibody 3	##	##	##	10	##	##	##	##	4	1	Move forward
Antibody 4	##	##	##	##	##	##	##	00	8	1	Move back
Antibody 5	##	##	##	##	00	##	##	##	5	#	Turn right 30°
Antibody 6	##	##	##	##	01	##	##	##	5	#	Turn right 30°
Antibody 7	##	##	01	##	10	##	##	##	5	#	Turn right 30°
Antibody 8	##	##	11	##	##	00	##	##	6	#	Turn right 60°
Antibody 9	##	##	##	01	##	10	##	##	6	#	Turn right 60°
Antibody 10	##	##	##	##	00	10	01	##	6	#	Turn right 60°
Antibody 11	##	11	##	##	##	##	00	##	7	#	Turn right 90°
Antibody 12	##	##	##	##	##	10	01	##	7	#	Turn right 90°
Antibody 13	##	##	##	01	00	##	00	##	7	#	Turn right 90°
Antibody 14	##	##	00	11	##	##	##	##	3	#	Turn left 30°
Antibody 15	##	##	01	##	##	##	##	##	3	#	Turn left 30°
Antibody 16	##	##	10	##	##	##	10	##	3	#	Turn left 30°
Antibody 17	##	00	##	11	11	##	##	##	2	#	Turn left 60°
Antibody 18	##	01	##	##	##	##	10	##	2	#	Turn left 60°
Antibody 19	00	10	##	##	##	01	##	##	2	#	Turn left 60°
Antibody 20	00	##	##	##	##	##	##	##	1	#	Turn left 90°
Antibody 21	01	##	##	11	11	##	##	##	1	#	Turn left 90°
Antibody 22	10	00	01	##	##	##	##	00	1	#	Turn left 90°

Fig. 6: Encoding definition of antibody in goal-oriented network

two parts: environment-oriented and goal-oriented network in this paper, the antibody concentration in two immune networks should be first calculated respectively, then the weighted sum of two antibody concentration is taken as the selection criteria. Below we will take the antibody in the environment-oriented network as an example to illustrate how to calculate the antibody concentration. The calculation of antibody concentration in goal-oriented network can be finished in the same way.

The antibody concentration in environment-oriented network mainly depends on the stimulation of antigen and the stimulation and suppression among 22 antibodies. In addition, according to the characteristics of biological immune system, the antibody will produce immune memory cells and save them in the body after the antibody is selected. When the robot meets with the similar environmental information, the historical selected antibody will be used again with higher probability. In this paper, the historical selected antibody is taken as the immune memory cell and is added in the immune network model to improve the path planning efficiency of mobile robot. The calculation of stimulation value and concentration of antibody i are described, respectively as follows:

$$\frac{dS_i^\circ(t)}{dt}=\left(\alpha\frac{\sum_{j=1}^{N}(m_{ji}^\circ a_j^\circ(t-1))}{N}-\alpha\frac{\sum_{k=1}^{N}(m_{ik}^\circ a_k^\circ(t-1))}{N}+\beta m_i^\circ+\theta T_i-k_i^\circ\right)\times a_i^\circ(t-1) \tag{1}$$

$$a_i^\circ(t)=\frac{1}{1+\exp(0.5-S_i^\circ(t))} \tag{2}$$

where, α and β are positive constants, N is the number of selected matching antibodies in 22 antibodies. The first term and second term in the bracket represent the stimulation level and suppression level that other antibodies spread to antibody i. m_{ji}° and m_i° represent the affinity between antibody j and antibody i and the affinity between antibody i and antigen respectively in environment-oriented network and are defined as follows:

$$m_{ji}^\circ=\sum_{t=1}^{8}\sum_{l=2t-1}^{2t}P_j^\circ(l)\oplus\overline{P_i^\circ(l)} \tag{3}$$

$$m_i^\circ=\sum_{t=1}^{8}\sum_{l=2t-1}^{2t}E^\circ(l)\oplus\overline{P_i^\circ(l)} \tag{4}$$

where, symbol $\oplus$' denotes exclusive-or operator. $P_j^\circ(l)$ and $P_i^\circ(l)$ represent the coding of paratope of antibody j and antibody i in environment-oriented network, respectively. $E^\circ(l)$ represents the coding of antigen.

The fourth term k_i° is the natural death of antibody i. The third term T_i represents the stimulation from the immune memory cell and θ is the adjustment coefficient. T_i depends on the frequency of usage of historical selected antibody i (F_i) and can be defined as follows:

$$T_i=F_i/\delta \tag{5}$$

where, δ is the adjustment coefficient.

In the same way, the concentration a_i^g of antibody i in goal-oriented network can also be calculated. The total concentration of antibody i is calculated as follows:

$$a_i = (1-\gamma_i)\cdot a_i^{o} + \gamma_i \cdot a_i^{g} \quad (6)$$

where, γ_i is the relative balance between the environment-oriented immune network and goal-oriented immune network.

Flow of the planning algorithm based on mutual-coupled immune network:

Step 1: Initialize the parameters of mutual-coupled immune network: initial stimulation values of all antibodies, α, β, θ, δ and so on

Step 2: Achieve the environmental information surrounding the robot through the robot sensors and finish the coding of antigen

Step 3: Find the number of robot sensor by which the detected obstacles is not in the near range and then select the matching antibodies whose paratopes regarding obstacle information are not 11 (namely near distance) according to the number of robot sensor

Step 4: Calculate the stimulation values and concentration of selected matching antibodies in environment-oriented according to Eq. 1-Eq. 5

Step 5: In the same way, calculate the stimulation values and concentration of selected matching antibodies in goal-oriented network

Step 6: Achieve the total concentration of selected matching antibody according to Eq. 6

Step 7: Select the optimal antibody whose total concentration is the largest and drive the robot according to the selected antibody (namely optimal behavior)

Step 8: Judge whether the robot has approached the goal. If done, finish the path planning; otherwise go to Step 2

SIMULATION EXPERIMENTS AND ANALYSIS

To verify the validity of proposed MMCINPA, selected tests in four static environments and one dynamic environment were implemented on an Intel Pentium IV 2.53 GHz computer with 2GB RAM using the MATLAB language. The test results are compared with Ishiguro's simple mutual-coupled immune network planning algorithm (SMCINPA).

In MMCINPA, $\alpha = 0.01$, $\beta = 0.25$, $\theta = 0.1$, $k_i = 0.05$, $\delta = [4,4,4,1,1,1,1,1,1,1,1,1,1,1,1,1,1, 1,1,1,1, 1,1]$ and $\gamma = 0.4$. In SMCINPA, $\alpha = 0.01$, $\beta = 0.5$, $\theta = 0.1$, $\gamma = 0.5$ and $k_i = 0.05$.

Test in static environments: The four static environments are shown in Fig. 7-10 and there are many obstacles with different shapes in them. The aim of the path planning is

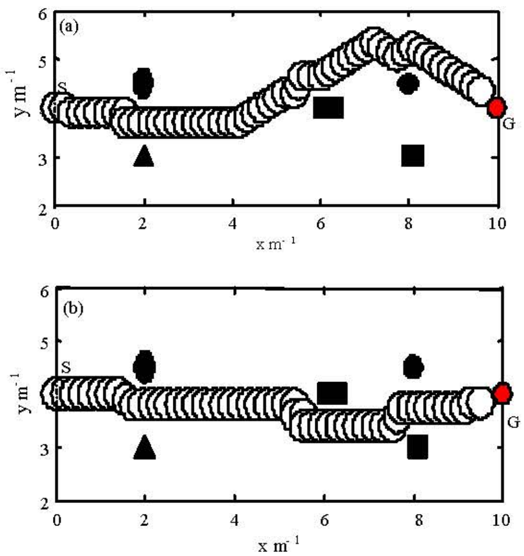

Fig. 7(a-b): Path planning results of two immune algorithms in static environment 1, (a) SMCINPA and (b) MMCINPA

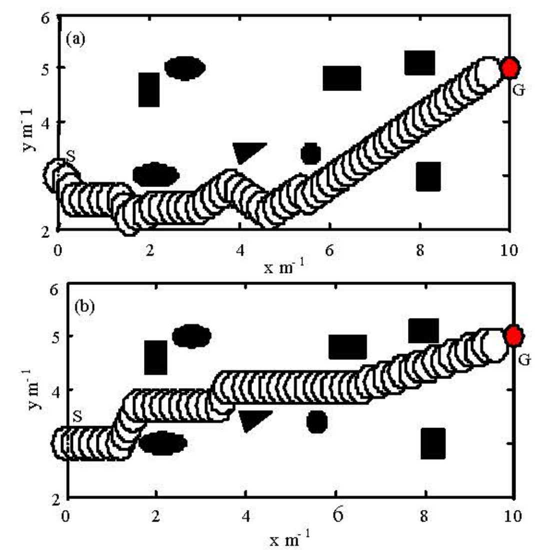

Fig. 8(a-b): Path planning results of two immune algorithms in static environment 2: (a) SMCINPA and (b) MMCINPA

to find a feasible path from the starting point S to goal G. From the test results of SMCINPA and MMCINPA in four static environments, it can be seen that these two immune network planning algorithms can find their own path in all environments, which fully demonstrates that the immune algorithm is characterized by the flexibility and robustness. However, if we have a further study on the

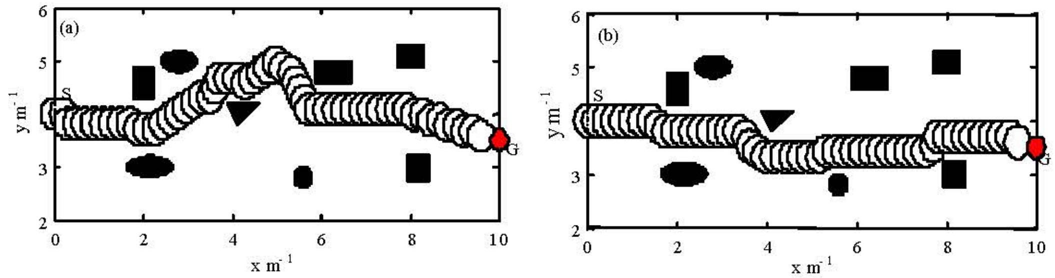

Fig. 9(a-b): Path planning results of two immune algorithms in static environment 3: (a) SMCINPA and (b) MMCINPA

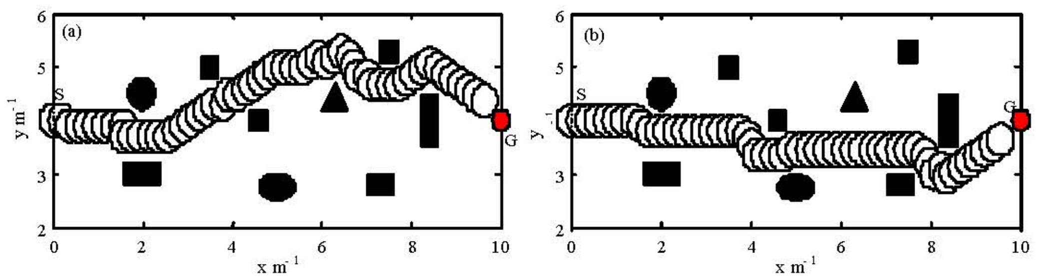

Fig. 10(a-b): Path planning results of two immune algorithms in static environment 4: (a) SMCINPA and (b) MMCINPA

Table 1: Performance comparisons between SMCINPA and MMCINPA in static environments

	Environment 1		Environment 2		Environment 3		Environment 4	
Performance	SMCINPA	MMCINPA	MCINPA	MMCINPA	SMCINPA	MMCINPA	SMCINPA	MMCINPA
Length of planned path(m)	10.8	10.2	11	10.4	10.8	10	11	10.4
Average turning angle	11.67°	11.17°	9.38°	5.45°	17.22°	11.76°	19.09°	10.96°

path planned by SMCINPA and MMCINPA, we are easy to find that the path planned by MMCINPA is smoother than that of SMCINPA, which is very important to the mobile robot and can improve the implementation efficiency of robot. From the planning results in four static environments, it can be seen that the proposed MMCINPA has better flexibility.

Table 1 further gives the concrete performance comparisons at the length of planned path and average turning angles of robot between SMCINPA and MMCINPA in four static environments. The average turning angle of robot reflects the smoothness of path. From the table, it can be obviously seen that the paths in MMCINPA are shorter and smoother than those in SMCINPA. Compared with the planning results of SMCINPA, the length of path planned by proposed MMCINPA shortens by about 5.97% and the average turning angle of path by MMCINPA decreases by about 30.11%. The enhancement of planning performance of MMCINPA is mainly due to two factors: One is the abundant antibodies; the other is the immune memory cells. In SMCINPA, there are only eight antibodies and the detection results of obstacles only are: existence and non- existence. It is very difficult for SMCINPA to find an optimal and smooth path in complicated environments. However, in the proposed immune planning model, there are 22 antibodies (namely robot behaviors) are designed and the detection results of robot sensors are divided into three degrees: far, middle and near. During the path planning in complicated environments, the robot can select more appropriate antibodies to avoid obstacles as well as reduce the turn as much as possible. The addition of immune memory cells regarding historical selected antibodies in the planning model improves the selection probability of historical antibodies in the same environment, which improves the planning efficiency and shortens the length of planned path.

Test in the dynamic environment: The test results of path planning in four static environments have verified the validity of proposed MMCINPA. In order to verify its validity in dynamic environments, we provide another

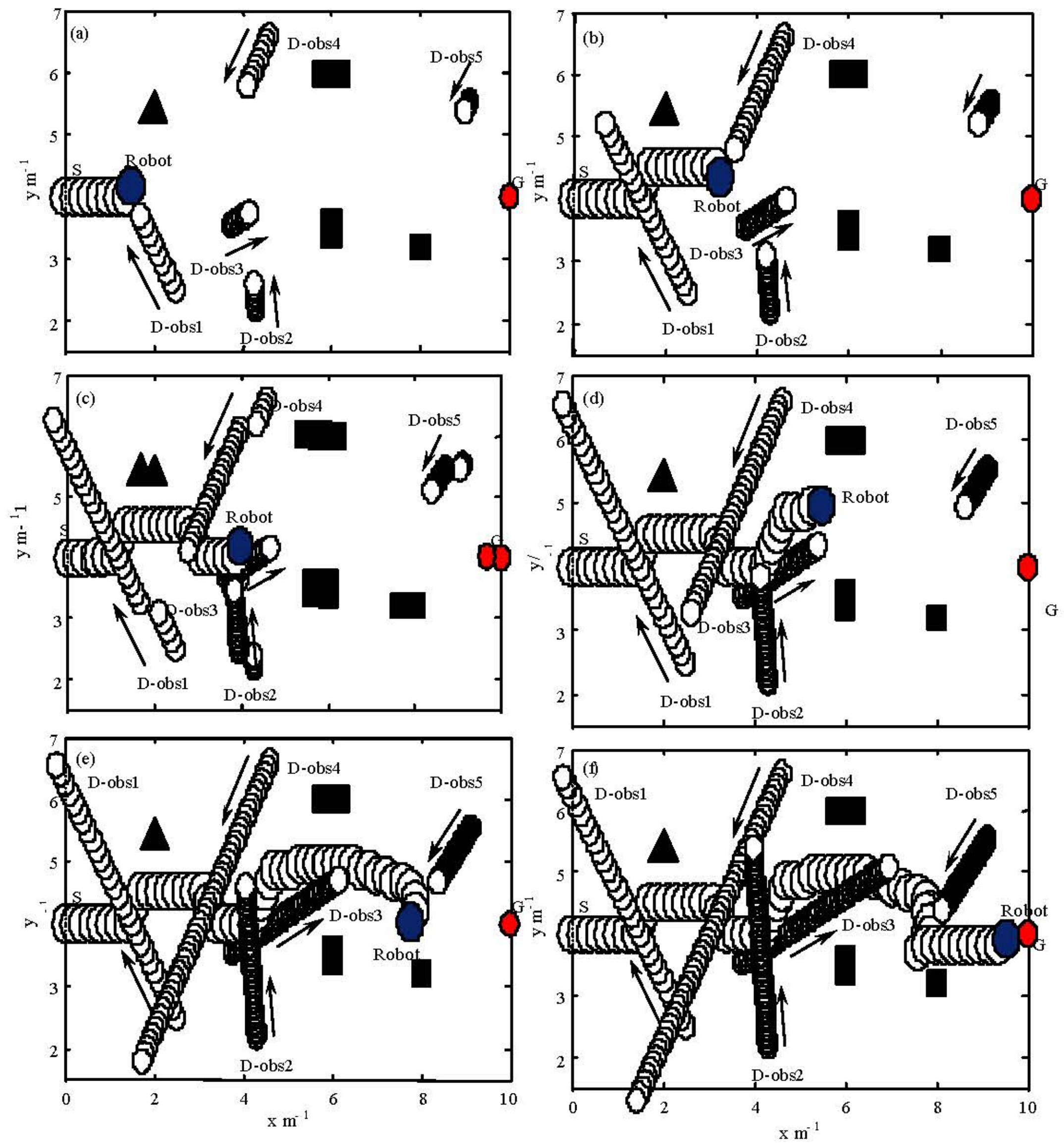

Fig. 11(a-f): Path planning results of MMCINPA in dynamic environment: (a) Status of avoiding D_obs1, (b)Status of avoiding D_obs2, (c) Status of avoiding D_obs3, (d) Status of avoiding D_obs4, (e) Status of avoiding D_obs5 (f) Status of reaching the goal

dynamic test. The dynamic environment is shown in Fig. 11, where there are some static obstacles and five dynamic obstacles moving from different directions with different velocities. Partial parameters of the dynamic environment are shown in Table 2.

The whole dynamic planning course is shown in Fig. 11. From the figure, it can be seen that the robot starts up from point $[0\ 4]^T$ and meets with D_obs1 first. The robot calculates the antibody concentration according to the environmental information and select antibody 19 to detour from the front of D_obs1, as shown in Fig. 11(a). After the robot avoids D_obs1, it enters the influence of three dynamic obstacles: D_obs2, D_obs3 and D_obs4 and the robot detours from the front of them again, as shown in Fig. 11b-d. After avoiding the four dynamic obstacles, the robot enters the environment of static obstacles and succeeds in avoiding static obstacles again through the antibody selection according to the antibody

Table 2: Partial parameters of the dynamic environment

			Dynamic obstacles				
Parameters	Robot	Goal	D_obs2	D_obs3	D_obs4	D_obs5	D_obs1
Initial position (m)	$[0, 4]^T$	$[10, 4]^T$	$[2.5, 2.5]^T$	$[4.3, 2.2]^T$	$[3.75, 3.55]^T$	$[4.6, 6.6]^T$	$[9.12, 5.54]^T$
Velocity (m·s-1)	$[0, 0.2]^T$	$[0, 0]^T$	$[-0.1, 0.15]^T$	$[-0.005, 0.05]^T$	$[0.05, 0.024]^T$	$[-0.06, -0.1]^T$	$[-0.0155, -0.018]^T$

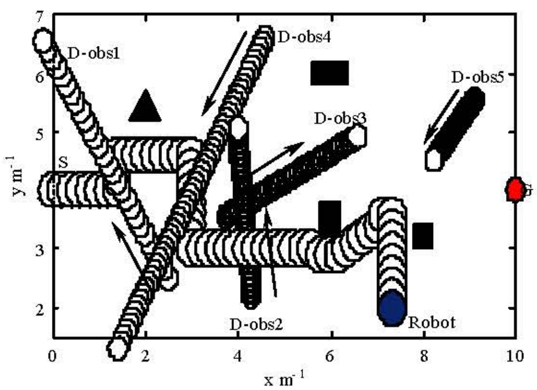

Fig. 12: Path planning results of SMCINPA in dynamic environment

concentration. After that, the robot meets with dynamic obstacle (namely D_obs5) again and avoids it successfully, as shown in Fig. 11e. Figure 11f shows that the robot has reached the goal successfully.

Figure 12 gives the planning results of SMCINPA in the same dynamic environment. From the figure, it can be seen that the robot can also detour D_obs1, D_obs2, D_obs3 and D_obs4 based on SMCINPA; however, it can not detour D_obs5 effectively. Contrast the dynamic planning results in Fig.11 with those in Fig. 12, we can further obviously see that the proposed MMCINPA has stronger planning performance and better robustness and can solve the path planning in unknown environments.

CONCLUSION

Path planning is one of the most important tasks in autonomous mobile robot navigation. In order to solve the problem in uncertain environments, we present a high efficient mutual-coupled immune network planning model on the basis of Ishiguro's immune network planning model. The following conclusions can be drawn from the theoretical analysis and simulation studies:

- According to the Jerne's idiotypic immune network hypothesis, we construct a mutual-coupled immune network for the mobile robot path planning. The network consists of environment-oriented network and goal-oriented network. The essence of path planning is to select an optimal antibody (namely robot behavior) in the mutual-coupled network to avoid the obstacles
- According to the needs of immune network planning model, we define the antibody structure. To improve the flexility of planning algorithm, the detection distance of each sensor is divided into three degrees: far, middle and near and 22 antibodies are designed for the path planning
- To further improve the planning efficiency of immune network planning model, the historical selected antibody is taken as the immune memory cell and its frequency of usage is added in the calculation of antibody concentration, which improves the selection probability of historical antibody in the same environment
- The selection of optimal antibody is based on the antibody concentration and the calculation model of antibody concentration is built on Farmer's dynamic model
- The test results in four static environments show that the paths planned by proposed MMCINPA are shorter and smoother than the paths planned by SMCINPA, which verifies the stronger planning ability and better flexility of MMCINPA. The test result in a dynamic environment shows that the robot based on proposed MMCINPA can detour all dynamic obstacles and static obstacles and eventually reach the goal successfully, which verifies the robustness of MMCINPA in the uncertain environments

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REFERENCES

Das P.K., S.K. Pradhan, S.N. Patro and B.K. Balabantaray, 2012. Artificial immune system based path planning of mobile robot. Soft Comput. Tech. Vision Sci., 395: 195-207.

Farmer J.D., N.H. Packard and A.S. Perelson, 1986. The immune system adaptation and machine learning. Phys. D: Nonlinear Phenomena, 22: 187-204.

Ge, S.S. and Y.J. Cui, 2002. Dynamic motion planning for mobile robots using potential field method. Auton. Robot, 13: 207-222.

Ishiguro, A., Y. Watanabe and Y. Uchikawa, 1995. An immunological approach to dynamic behavior control for autonomous mobile robots. Proceedings of the 1995 IEEE/RSJ International Conference on Intelligent Robots and Systems, August 5-8, 1995, Pennsylvania, USA., pp: 495-500.

Jerne, N.K., 1973. The immune system. Scientific Am., 229: 52-60.

Jerne, N.K. and J. Cocteau, 1984. Idiotypic networks and other preconceived ideas. Immunol. Rev., 79: 5-24.

Lu Z., L. Li and Y.B. Zou, 2012. Research of mobile robot path planning based on immune algorithm. Machine Tool Hydraulics, 11: 25-28.

Song, G.Y., 2013. Self-localization system of the explosive ordnance disposal robot based on danger model immune wavelet neural network. Int. J. Digit. Content Technol. Appl., 7: 643-651.

Song, L.L., 2012. Navigation control of an autonomous robot based on chaos immune optimization algorithm. Adv. Inform. Sci. Serv. Sci., 5: 302-310.

Tan Y.L., Y.J. Fang and J.P. Yu, 2012. Application of improved immune algorithm to multi-robot environment exploration. Int. J. Adv. Comput. Technol., 4: 158-164.

Wang, Y.Y., T.T. Wei and X.J. Qu, 2012. Study of multi-objective fuzzy optimization for path planning. Chin. J. Aeronaut., 25: 51-56.

Yuan, M.X., S.A. Wang, C.Y. Wu and K.P. Li, 2009. APF-guided adaptive immune network algorithm for robot path planning. Front. Comput. Sci. China, 3: 247-255.

Yuan, M.X., S.A. Wang, C.Y. Wu and K.P. Li, 2010a. Hybrid ant colony and immune network algorithm based on improved APF for optimal motion planning. Robotica, 28: 833-846.

Yuan, M.X., S.A. Wang, C.Y. Wu and N.J. Chen, 2010b. A novel immune network strategy for robot path planning in complicated environments. J. Intell. Robot Syst., 60: 111-131.

Yuan, M.X., Z.L. Ye, S. Cheng, S.A. Wang and Q. Wang, 2012. A novel small-world algorithm incorporating chaos optimization and its application to robot path planning. Proc. Inst. Mech. Eng. Part I J. Syst. Control Eng., 226: 1356-1370.

Zhao, S.G. and M. Li, 2010. Path planning of inspection robot based on ant colony optimization algorithm. Proceedings of the International Conference on Electrical and Control Engineering, June 26-28, 2010, Wuhan, China, pp: 1474-1477.