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Artificial Immune Algorithm based Robot Obstacle-Avoiding Path Planning

Zeng Dehuai[1,2], Xu Gang [2,3] , Xie Cunxi[1], Yu degui [2]
1South China University of Technology, Guangzhou, Guangdong, 510640, China
2 Institute of Intelligent Technology, Shenzhen University, 518060,China
3 Shenzhen Key laboratory of mould advanced manufacture

Abstract **- Planning of the optimal path has always been the target pursued by many researchers, and its application in mobile robot is one of the most important research topics. This paper aims to plan the obstacle-avoiding path for mobile robots based on the Artificial Immune Algorithm (AIA) developed from the immune principle. This paper analyzes the motion characteristic of the car-like autonomous mobile robot. An immunity algorithm adapting capabilities of the immune system is proposed and enable robot to reach the target object safely and successfully fulfill its task through optimal path and with minimal rotation angle efficiency. Simulation results show that the mobile robot is capable of avoiding obstacles, escaping traps, and reaching the goal efficiently and effectively.**

Index Terms – Artificial immune algorithm, path planning, optimal path, obstacle avoiding

I. INTRODUCTION

Autonomous mobile robots have a wide range of applications in industries, hospitals, offices, and even the military, due to their superior mobility. Some of their capabilities include automatic driving, intelligent delivery agents, assistance to the disabled, exploration and map generation for environmental cleanup, etc. The ultimate goal of robotics is to build artificial agents capable of displaying rational and complex behaviors in the accomplishment of a specific task. The tasks under consideration are characterized by the need of meaningful interactions of the agent with a real dynamic world through a physical body. The achievement of this goal requires the development of a series of innovative technologies and an extensive effort on research in areas such as artificial intelligence and emergent computing.

In order to adapt the robot’s behavior to any complex, varying and unknown environment without further human intervention, intelligent mobile robots should be able to extract information from the environment, use their built-in knowledge to perceive, act and adapt within the environment. They move and plan their actions to accomplish objectives defined either extrinsically by a human programmer or intrinsically on the basis of a general objective of survival. As a result, path planning of intelligent robot behavior plays an important role in the development of flexible automated systems. The design goal for path planning is to enable a mobile robot to navigate safely and efficiently without collisions to a target position in an unknown and complex environment.

Planning of the optimal path has always been the target pursued by many researchers, and its application in mobile robot is one of the most important research topics! In the literature [1~3] many methods have been proposed to tackle this problem, such as the grid algorithms, potential field methods, neural network methods and genetic algorithm approaches. Each method has its own strength over others in certain aspects, for example, the route of the grid algorithm might not be feasible, or non-optimum in the route. The potential field of the tendency has some extreme points. The planning time of the genetic algorithm is too long; neural network is difficult to the space where the sample does not distribute. Researchers have always been seeking alternative and more efficient ways to solve the problem.

In the last decade, it has been shown that the biologically inspired artificial immune system (AIS) has a great potential in the fields of machine learning, computer science and engineering [4–7]. Dasgupta [4] summarized that the immune system has the following features: self-organizing, memory, recognition, adaptation, and learning. There are a lot of researches investigating the interactions between various components of the immune system or the overall behaviors of the systems based on an immunological point of view. The immune systems provide an excellent model of adaptive process operating at the local level and of useful behavior emerging at the global level [4, 9]. Accordingly, the artificial immune system can be expected to provide various feasible ideas for the applications of mobile robots [10–12].

A plan on obstacle-avoiding path for mobile robots based on artificial immune algorithm is constructed in this study. The application task for the mobile robot is to navigate in an unknown and complex environment while avoiding static obstacles but reaching a goal safely. The basic concept of the proposed scheme is described in the following sections. The related biological immune system is described in Section 2, whereas Section 3 presents the developed methodology of AIA in detail. Section 4 illustrates the effectiveness of the proposed methodology through some simulations. Finally, Section 5 concludes the paper.

II. BIOLOGICAL IMMUNE SYSTEM

A. Concept of Immune System

Biological immune system is a highly evolved, complicated adaptability system in the body of advanced spinal animals, which can identify and resist antigenic foreign bodies like bacteria and viruses and maintain the stability of the in vivo environment. The body identifies invading antigens through two inter-related system: the innate immune system and the adaptive immune system. The basic

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components of the immune system are lymphocytes that occur as two major categories, namely B-cell and T-cell, play a remarkable role in both immunities [13]. B-cells take part in humoral immunity that secrete antibodies by the clonal proliferation, and T-cells take part in cell mediated immunity. One class of the T-cells, called the Killer T-cells, destroys the infected cell whenever it recognizes the infection. The other class that triggers clonal expansion and stimulates or suppresses antibody formation is called the Helper T-cells. Each of B-cells has distinct molecular structure and produces 'Y' shaped antibodies from its surfaces. The antibody recognizes antigen that is foreign material and eliminates it. This antigen-antibody relation is innate immune response.

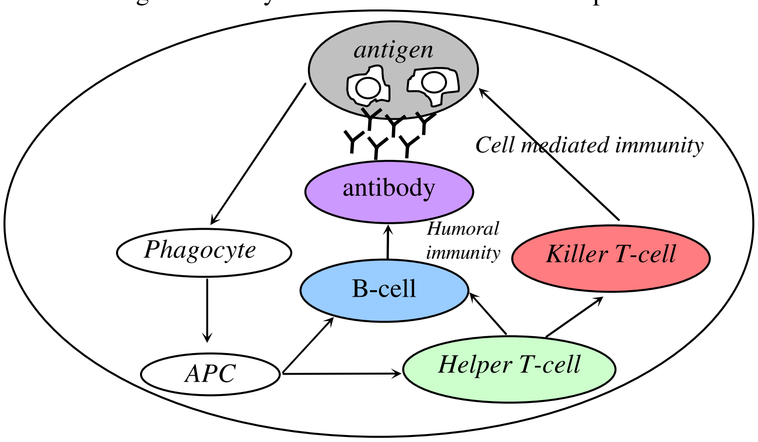


Fig. 1 Illustration of the biological immune system

Fig. 1 depicts the model describing the relationship between components on the immune system. When an infectious foreign pathogen attacks the human body, the innate immune system is activated as the first line of defense. Innate immunity is not directed in any way towards specific invaders but against any pathogens that enter the body. It is called the non-specific immune response. The most important cell in innate immunity is a phagocyte including monocytes, macrophages, etc. The phagocyte internalizes and destroys the invaders to the human body. Then the phagocyte becomes an Antigen Presenting Cell (APC). The APC interprets the antigen appendage and extracts the features by processing and presenting antigenic peptides on its surface to the T-cells and B-cells.

These lymphocytes will be sensitive to this antigen and be activated. Then the Helper T-cell releases the cytokines, which are the proliferative signals acting on the producing B-cell or remote the other cells. On the other hand, the B-cell becomes stimulated and creates antibodies when it recognizes an antigen. Recognition is achieved by intercellular binding, which is determined by molecular shape and electrostatic charge. The secreted antibodies are the soluble receptor of B-cells and these antibodies can be distributed throughout the body [14]. An antibody's paratope can bind an antigen's epitope according to its affinity. Moreover, B-cells are also affected by Helper T-cells during the immune responses [15]. The Helper T-cell plays a remarkable key role in determining whether the immune system uses cell-mediated immunity (by Th1 Helper T-cells) or humoral immunity (by Th2 Helper T-cells) [13], and connects the non-specific immune response to make a more efficient specific immune response.

The immune system produces the diverse antibodies by recognizing the idiotype of the mutual receptors of the antigens between antigen and antibodies and between antibodies. The relation between antigens and antibodies and that amongst antibodies can be evaluated by the value of the affinity. In terms of affinities, the immune system self-regulates the production of antibodies and diverse antibodies. Affinity maturation will occur, when the maturation rate of a B-cell clone increases in response to a match between the clone's antibody and an antigen. Those mutant cells are bound more tightly and stimulated to divide more rapidly. Affinity maturation dynamically balances exploration versus exploitation in adaptive immunity [16]. It has been demonstrated that the immune system has the capability to recognize foreign pathogens, learn and memorize, process information, and discriminate between self and non-self [13, 16].

B. *Idiotopic Network*

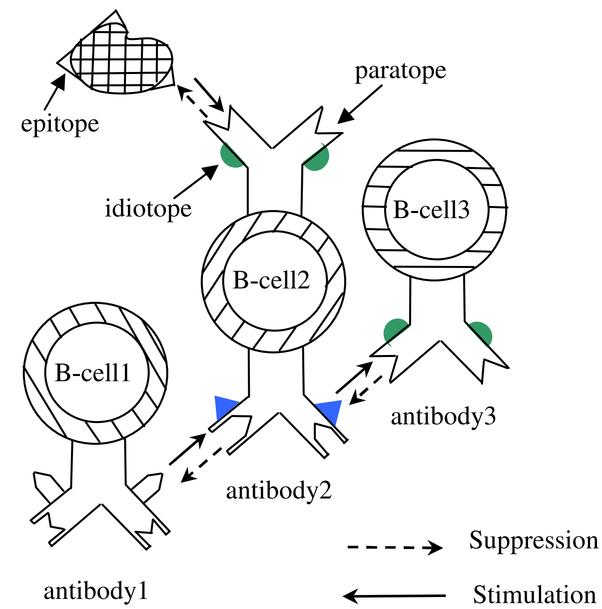


Fig. 2 Jerne's idiotopic network hypothesis

III. Modeling of AIA Based Robot Path Planning

Artificial immune network is applied in robot path planning. The detailed description of each element is presented below.

A. Problem Representation

To validate AIA for the mobile robot path planning, the car-like wheeled mobile robot is used as object investigated, showed as in fig.3. The robot has four wheels, the rear wheel can be steered while the front wheel is used to orient. The robot has sensors capable of determining the relative position obstacles and targets, perceiving environment information. According to [17], when the speed is not too quick, the car with four wheels can be regard as the model of two wheels car. The model is depicted in Fig. 4, thus

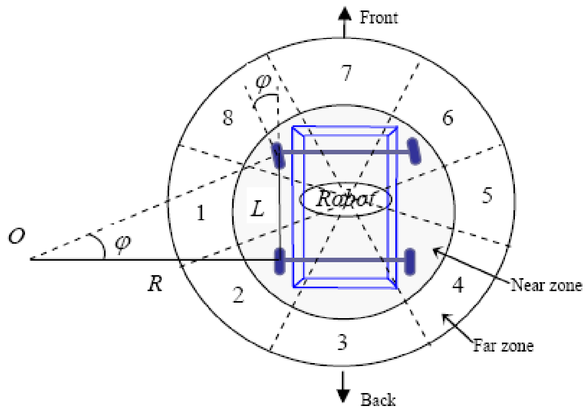


Fig.3 Configure of Car-like wheeled robot

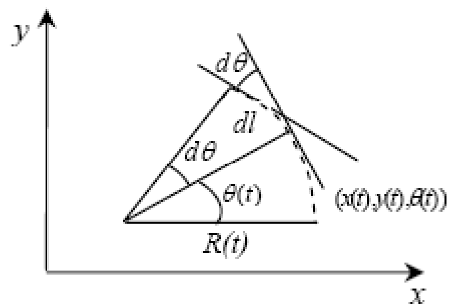


Fig.4 Kinematics Model of the mobile robot

$$R = dl / d\theta = V(t)dt / d\theta = V(t)/(d\theta / dt) = V(t)/\dot{\theta}(t) \quad (1)$$

$$tg\varphi = L / R \quad (2)$$

Where, R is the steering radius; L designating the distance between the front axle and the real axle; φ is the steering angle; V is the steering velocity; θ is the orientation of the robot. R in equation (2) is replaced by formula (1), then

$$\dot{\theta}(t) = (tg\varphi) \times (V(t)/L) \quad (3)$$

$$\theta(t) = \theta_0 + \frac{1}{L}\int_0^t tg\varphi(t)V(t)dt \quad (4)$$

Here, $\dot{\theta}(t)$ denotes the orientation rate of the car. According to mobile robot kinematics model shown as in fig.4, $dx = dl \cdot \cos\theta,\ dy = dl \cdot \sin\theta$, and in formula (1), we can know $dl = V(t)dt$, then

$$x(t) = x_0 + \int_0^t V(t) \cdot \cos\theta(t)dt \quad (5)$$

$$y(t) = y_0 + \int_0^t V(t) \cdot \sin\theta(t)dt \quad (6)$$

Thus, formula (4) ~ (6) depict the kinematics model of four wheeled mobile robot, where (x_0, y_0, θ_0) denoting the start point position and orientation, $(x(t), y(t), \theta(t))$ corresponding to the robot position and orientation at t time.

B Definition of Antigen and Antibody

The objective of the system is for robot to find an optimal obstacle free path, the task is spread out in the environment. When environment changes occur, the mobile robot can adapt itself to new situation rapidly. This algorithm is modeled based on clonal selection and immune network hypothesis.

Definition of the antigen

According to the distribution of task, the density of plan on obstacle-avoiding path is divided into three levels that are high, low and nothing. For each of these environments, a robot faces with several strategies that are turning, back-forwarding, straight moving, random moving, and so on.

Definition of the antibody

Antibody is defined as the current environment of the mobile robot, including the distance of between the robot and the obstacles, relative orientation of the robot. Definition of antibody is depicted in Fig.5 [18,19]. Condition1 is composed of two parts. One part represents the distance between the robot and the target, the other stands for the angle between the robot and the target. Condition2 is also composed of two parts. One part stands for the distance between the robot and obstacles, another part stands for the angle between the robot and obstacles. Since the mobile robot is composed of 8 sensors to detect the distance and angle between the robot and the obstacle or the goal, shown as Fig.3. Every include angle of the robot 45°, therefore, action denotes the direction of the robot that may have eight directions (forward, left, left forward, right, right forward, left back, right back, back).

condition		*Action*
condition1	*Condition2*	*8 direction moving*

Fig.5 Definition of one antibody

C Modeling of Antibodies-antigen Mutual action

The immune networks are divided into two categories. One part is between the mobile robot and the obstacle in the immune network a_i^o, the other is between the mobile robot and the goal of the immune network a_i^g. The antibody a_i is defined as follows [20]:

$$a_i = (1 - \gamma_i) \cdot a_i^o + \gamma_i \cdot a_i^g \quad (7)$$

where γ_i is the ratio between antibody a_i^o and antibody a_i^g.

The antibody with the highest a_i is selected γ_i is:

$$\gamma_i = \begin{cases} \dfrac{d_g}{d_o + d_g}, & d_g > d_o \\ \dfrac{d_o}{d_o + d_g}, & d_g < d_o \\ 1, & only\ d_g \end{cases} \quad (8)$$

Where d_g and d_o are the distance of the goal to the mobile robot and the obstacle to the mobile robot. When d_g exceeds d_o, the numerator is d_g, otherwise, the numerator is d_o. If the robot is detected only at the goal, then γ_i equals 1. The obstacle antibody antibody a_i^o and the goal antibody a_i^g in an immune network are derived as follows [21]:

$$\begin{aligned} a_i^o &= \left(\frac{\sum_{l=1}^{N_{Ab}} m_{il}^{ost}\cdot a_l^o}{N_{Ab}} - \frac{\sum_{k=1}^{N_{Ab}} m_{ki}^{osu}\cdot a_l^o}{N_{Ab}} + m_i^o - k_i^o\right)\cdot a_i^o \\ &= [(m_{i1}^{ost}\cdot a_1^o + m_{i2}^{ost}\cdot a_2^o + \cdots + m_{iN_{Ab}}^{ost}\cdot a_{N_{Ab}}^o)/N_{Ab} \\ &\quad - (m_{1i}^{osu}\cdot a_1^o + m_{2i}^{osu}\cdot a_2^o + \cdots + m_{N_{Ab}i}^{osu}\cdot a_{N_{Ab}}^o)/N_{Ab} \\ &\quad + m_i^o - k_i^o]\cdot a_i^o \\ &= \{[(m_{i1}^{ost} - m_{1i}^{osu})\cdot a_1^o + (m_{i2}^{ost} - m_{2i}^{osu})\cdot a_2^o + \cdots \\ &\quad + (m_{iN_{Ab}}^{ost} - m_{N_{Ab}i}^{osu})\cdot a_{N_{Ab}}^o]/N_{Ab} + m_i^o - k_i^o\}\cdot a_i^o \\ &= [(m_{i1}^{oss}\cdot a_1^o + m_{i2}^{oss}\cdot a_2^o + \cdots + m_{iN_{Ab}}^{oss}\cdot a_{N_{Ab}}^o)/N_{Ab} \\ &\quad + m_i^o - k_i^o]\cdot a_i^o \\ &= \left(\sum_{l=1}^{N_{Ab}} m_{il}^{oss}\cdot a_l^o/N_{Ab} + m_i^o - k_i^o\right)\cdot a_i^o \end{aligned} \tag{9}$$

$$\begin{aligned} a_i^g &= \left(\frac{\sum_{l=1}^{N_{Ab}} m_{il}^{gst}\cdot a_l^g}{N_{Ab}} - \frac{\sum_{k=1}^{N_{Ab}} m_{ki}^{gsu}\cdot a_l^g}{N_{Ab}} + m_i^g - k_i^g\right)\cdot a_i^g \\ &== \left(\sum_{l=1}^{N_{Ab}} m_{il}^{gss}\cdot a_l^g/N_{Ab} + m_i^g - k_i^g\right)\cdot a_i^g \end{aligned} \tag{10}$$

where $i,l,k = 0,1,\ldots,N_{Ab}$ is are the subscripts to distinguish the antibody types and N_{Ab} is the number of antibody. Eq.(9) is composed of four terms. The first term on the right hand shows the degree of stimulation by other antibodies, while the second term depicts the suppressive interaction between the antibodies. The third term represents the external input from the antigents. and the final term is the natural extinction term, which indicates the dissipation tendency in the absence of any interaction. a_i^o and a_i^g can be calculated using similarly method. m_{il}^{ost} and m_{ki}^{osu} indicate the obstacle stimulative and suppressive affinity between the *i*th and the *l*th, *k*th antibodies, respectively. m_i^o and m_i^g denote the affinity of antigen and antibody, k_i^o and k_i^g represent the natural death coefficient.

$$\alpha_o = \frac{D - d_o}{D} \tag{11}$$

$$m_{il}^{oss} = \begin{cases} \dfrac{m_{il}^{oss}}{1-\alpha_o}, & d_o > d_{set} \\ \dfrac{m_{il}^{oss}}{\alpha_o}, & d_o < d_{set} \end{cases} \tag{12}$$

$$\alpha_g = \frac{D - d_g}{D} \tag{13}$$

$$m_{il}^{gss} = \begin{cases} \dfrac{m_{il}^{gss}}{1-\alpha_g}, & d_g > d_{set} \\ \dfrac{m_{il}^{gss}}{\alpha_g}, & d_g < d_{set} \end{cases} \tag{14}$$

where D is the maximum size of the limited area. d_o is the distance between the robot and the obstacle. d_{set} is the radius of the robot required to avoid the obstacle.

D AIA based Algorithm for Mobile Robot Path Planning

When the robot gets the task, it saves the start point and goal point information. The flow chart of the algorithm can be depicted as Fig. 6.

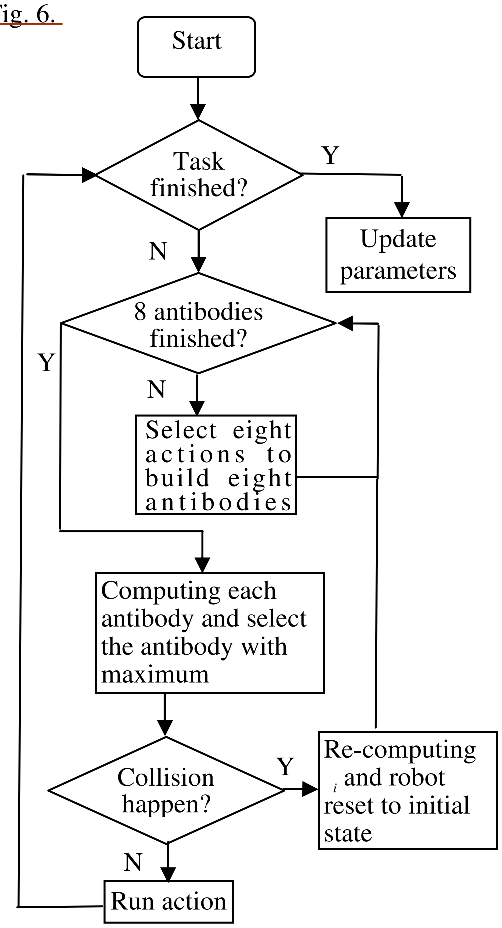


Fig. 6 The flow chart of AIA algorithm

IV. Simulation Results and Discussions

The simulation conditions for verifying the effectiveness of the proposed artificial immune algorithm are set as follows. The mobile robot work space of 2 [m]×2[m] wide. The size of robot is 60[mm] in diameter.

This simulation experiment mainly aims to compare and analyze the differences between the artificial immune research method, and the genetic algorithm (GA) proposed by Lu [22], and present the experiment results. Mobile robot needs to avoid five static obstacles to reach the target object and fulfill its task.

A Comparison between AIA and GA simulation

Fig. 7 "○" is the AIA simulation result of the eighth generation number of the mobile robot, and 54 steps will be needed before reaching the target object. Fig. 7 "□" is the GA simulation drawing proposed by Lu. This is the simulation result of the eighth generation number of the mobile robot, and 68 steps will be needed before reaching the target object.

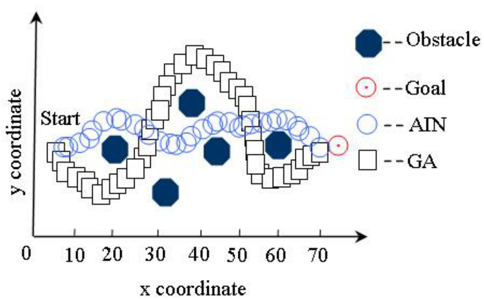
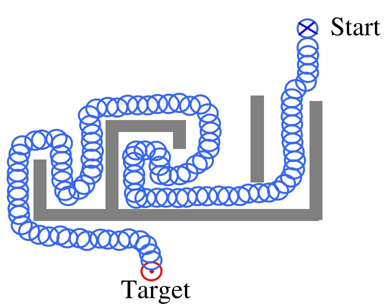


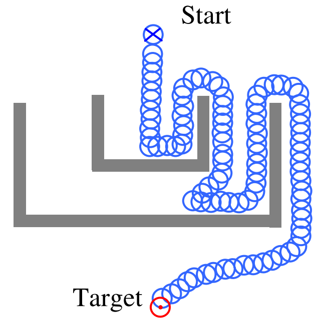
Fig. 7 Obstacle avoiding path planning of mobile robot

B. Path planning to escape from loop type and double-U trap

Assuming that the robot has eight uniformly distributed distance sensors (i.e. $N_s = 8$) and eight moving directions including forward, left, right, back, forward left, forward right, back left, and back right (i.e. $N_{Ab} = 8$). Fig. 8 (a) demonstrates the trajectory of the mobile robot to escape from loop-type and dead-end-type trapping situations. At the same time, the most famous and utilized example in mobile robot navigation, U-shaped trap problem, is employed in this study. Fig. 8 (b) shows part of the paths of the robot escaping from the U-shaped trap. Apparently, AIA successfully drives the robot to escape the double U-shaped trap.



(a) Escape approach from loop and dead-end trap



(b) Escape approach from double U-shaped trap

Fig.8 Robot trajectories to escape trap situation

C. Discussion

The results of simulation experiment of this study shows that the artificial immune robot can efficiently reach the destination in a complicated environment. And the expectation mechanism and adaptation mechanism designed are both effective. The results show that the artificial immune robot can quickly adapt to the environment, and after learning, it can also avoid obstacles to approach the target object via the shortest path.

V Conclusions

Algorithms based on the biological system are a major topic in current researches and applications of computer intelligence. A method of robot path planning inspired by the biological immune system is developed in this paper. To verify the effectiveness of our method, the proposed method is applied to mobile robot environment with several obstacles and in the double U-shaped environment, respectively. Simulation results indicate that presented method has same capability of obtaining an optimal or near-optimal collision free path planning as GA proposed in [8]. Several trap environments employed in early studies are employed to evaluate the performance of the proposed methodology. Simulation results validate the flexibility, efficiency and effectiveness of the robot navigation algorithm, especially the solution of the local minima problem. Future researches will be directed to more complicated environments and assignments of tasks for the mobile robot to fulfill.

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