An Immunity Algorithm for Path Planning of the Autonomous Mobile Robot

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Abstract—**This paper analyzes the moving characteristic of the car-like autonomous mobile robot. An immunity algorithm adapting capabilities of the immune system is proposed and applied to solve the path planning and optimizing of the autonomous mobile robot. The simulation results validate several significant characteristics of the immunity algorithm: adaptability, learning, flexibility, and intelligence.**

Index Terms—**Autonomous mobile robot; Immune system; kinematics model**

I. INTRODUCTION

Path planning is a hot question in robotic artificial intelligence. According to the technology adopted, modern path planning method divides into two big classes: global path planning and local path planning. The methods include the grid algorithm, the potential field [1], the genetic algorithm [2], neural network [3], etc... Though each there is a advantage, there are a lot of defects, 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 space where sample does not distribute. Through combination of the movement characteristic of the robot and the immune algorithm, we designed the path planning algorithms based on the immune network theory. Through studying the Algorithm can obtain rule, and define rule. It has strong ability of space searching and regular discovering and learning ability. It has higher intelligence and flexibility... The robot makes satisfied planning solve set from environmental space to instruction space very fast by the algorithm.

II. THE BIOLOGICAL IMMUNE SYSTEM

The immune system protects living bodies from the invading of foreign substances such as viruses, bacteria, and other parasites (called antigens). There are two types of immunity in the human body, the humoral immunity and the cell mediated immunity. Two main types of lymphocyte, namely B-cell and T-cell, play a remarkable role in both immunities [4]. The former take part in the humoral immunity that secretes antibodies by the clonal proliferation while the latter take part in cell mediated immunity. One class of the T-cells, called the Killer T-cells, destroys the infected cell whenever they recognize the infection. The other class, which triggers clonal expansion and stimulates/suppresses antibody formation, is called the Helper T-cells. Lymphocytes float freely in the blood and lymph nodes. They patrol everywhere for foreign antigens, then gradually drift back into the lymphatic system, to begin the cycle all over again.

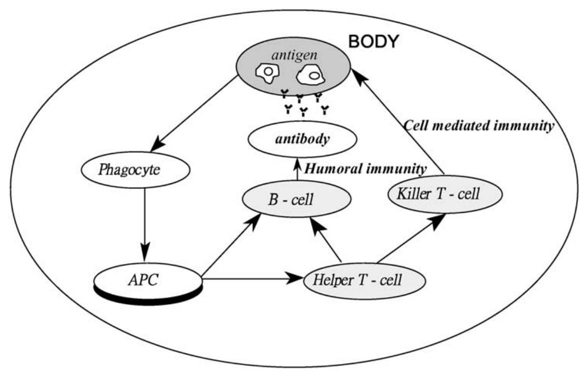


Fig. 1 Illustration of the biological immune system

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, rather against any pathogens that enter the body [4]. It is called non-specific immune response. The most important cell in the innate immunity is the phagocyte, which includes monocytes, macrophages, etc. Phagocytes internalize and destroy 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-cell and B-cell. These antigenic peptides are a kind of molecule called MHC (major histocompatibility complex) to distinguish a 'self' from other 'non-self' (antigen) [5].

These lymphocytes will be sensitive to these antigens and become activated. Then the Helper T-cell releases the cytokines, which are the proliferate signals acting on the producing B-cell or the other remote cells. On the other hand, B-cell becomes stimulated and creates antibodies when a B-cell recognizes an antigen. Recognition is achieved by inter-cellular binding, which is determined by molecule shape and electrostatic charge. The secreted antibodies are the soluble receptors of B-cell and these antibodies can be distributed throughout the body [5]. An antibody's paratope can bind with an antigen's epitope according to their affinity. Moreover, B-cells are also affected by Helper T-cells during the immune responses [7]. The Helper T-cell plays a remarkable key role in determining the immune system towards either the cell mediated immunity (by Th1 Helper T-cells) or the humoral immunity (by Th2 Helper T-cells) [4], and connects the non-specific immune response to make a more efficiency-specific immune response.

When the maturation rate of a B-cell clone increases in response to a match between the clone's antibody and an antigen, affinity maturation occurs. Those mutant cells are bound more tightly and stimulated to divide more rapidly. Affinity maturation dynamically balances exploration versus exploitation in adaptive immunity [6]. 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 [6 and 4].

III. DEPICT SYSTEM

The autonomous mobile robot is car-like wheeled mobile robots which have four wheels, the rear-wheel driven car. The rear wheel can be steered while the front wheel orientation. The robot has sensors capable of determining the relative position obstacles and targets, have knowledge of their position, and environments. We divide the robot into 8 parts from the center, and coding from 1 to 8 as shown in Fig. 2. We dived the distance into far and close, thus robot can get the environment information in 8 directions. According to [8], the kinematics model of four wheeled mobile robots depict in (1).

$$\begin{cases} x(t) = x_0 + \int_0^t \cos\theta(t)V(t)dt \\ y(t) = y_0 + \int_0^t \sin\theta(t)V(t)dt \\ \theta(t) = \theta_0 + \frac{1}{L}\int_0^t tg\phi(t)V(t)dt \end{cases} \quad (1)$$

Where L designating the distance between the front axle and the rear axle; R is the steering radius; ϕ is the steering angle; V is the steering velocity; (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 time. t.

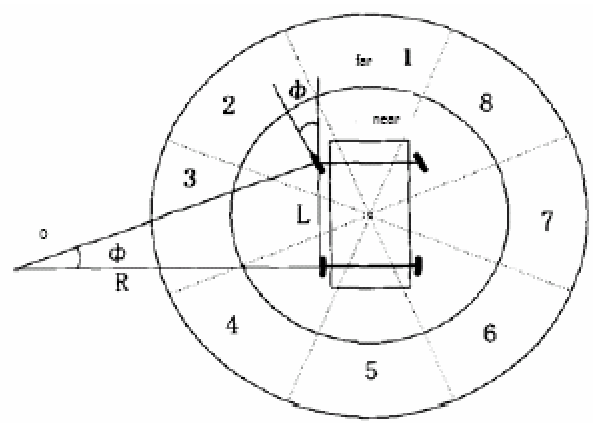


Fig.2 Robot information distribution and gesture diversion.

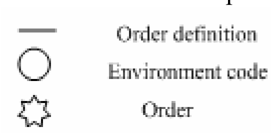
IV. ALGORITHM DESCRIPTION

We depict the robot path planning as following: in a certain E space, the robot can obtain I_{t1} and I_{t2} at time t in exploring scope, I_{t1} is the position and gesture of the robot to the obstacle, I_{t2} is the position and gesture of robot to the target. The robot should find an optimal path from start point to target point avoiding the obstacles. The robot find an instruction sequence [c_t] to accomplish the task in the instruction s space R essentially.

We assume that the most control times from robot to the target are L , and the instruction number is K in instruction space C . If the instruction time of optimal path to the target is l , the random probability to get the optimal path can be obtained from equation (2).

$$P = \frac{1}{L}\left(\frac{1}{K}\right)^l \quad (2)$$

A lot of possibilities can be eliminated in searching the optimal path. For example, when there is an obstacle in front of the robot, the instruction "forward" is impossible. If we introduce rules, we can improve the possibilities in searching the optimal path. The robot get information from the environment is limited and fuzzy, the decision system is not flexible. The artificial immune system can learn and have the advantage of fuzzy rules, so we introduce it to solve the autonomous mobile robot path planning.



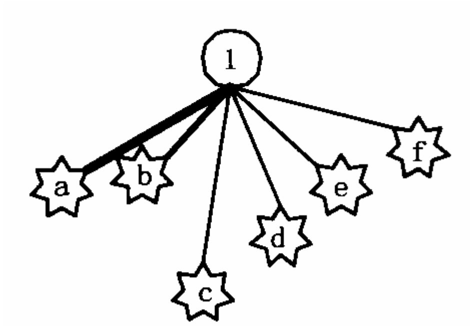


Fig.3. The structure of antibody

We define antibody as Fig.3, antibody an including environments codes and control instruction s. Environment code I_t is composed of I_{t1} and I_{t2} at time t and coded in binary. I_{t1} is the position and gesture of the robot to the obstacle, I_{t2} is the position and gesture of robot to the target. {a,b,c,d,e,f} in instruction set represents the six robot instruction {forward, left forward, right forward, left back, right back, back}; {S} which means stop is the terminate point of the antibody network. Instruction definition η_i (i=0…5) show the

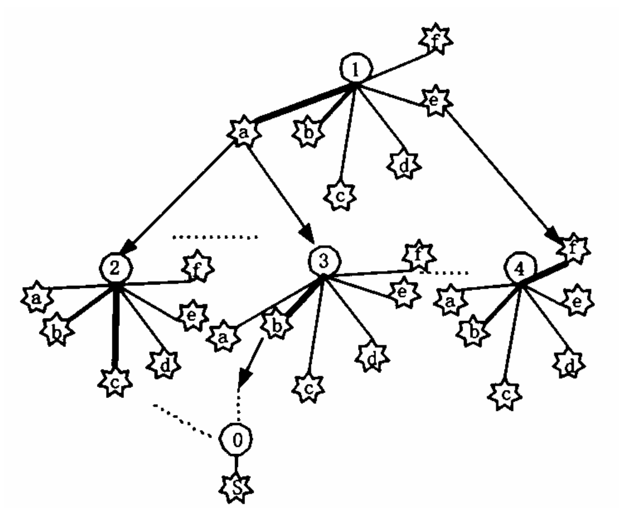


Fig.4 The relation network of antibody.

possibility of robot executing the instruction. The thicker the line in the graph, the higher the instruction definition and the instruction validity. The robot track is depicted by antibody in Fig. 4. One antibody can reach to different antibody according to the instruction and the environment. The relationship between the antibodies is not fixed. The antibody will reach different antibody at same instruction even in different environment. The essence of Path planning is to find a graph consists of the antibody, and the graph show the optimal path of the robot.

Instruction definition η_i in the antibody can be obtained from equation (3), where α_i is the number of executing the instruction.

$$\eta_i = \frac{\alpha_i}{\sum_{j=0}^{5} \alpha_i} \quad i=0\ldots5 \qquad (3)$$

The vitality of antibody is dispatched as δ. When δ=0, the antibody is die. The vitality of antibody δ can be obtained from equation (4), where a denotes the number of activated antibody; and k is the adjusted coefficient.

$$\delta = \frac{1}{1-e^{-ka}} \qquad (4)$$

The fitness ζ of outer environment and environment codes in the antibody pool can be obtained from equation (5), where I_t is the environment binary code, A is the antibody environment binary code segment, and N is the length of the environment code.

$$\zeta = \frac{\sum_{i=0}^{N} I_{ti} * A_i}{N} \qquad (5)$$

When the robot gets the task, it saves the start point state information. The flow chart of the algorithm can be depicted as Fig.5.

(1) Start;

(2) Check whether the task has finished or not, if finished, jump (3)

(2.1) Check the robot's state and obtain the environment codes I_t Ii at this moment; check whether the robot will collide or not. If collided, resetting system (Resume the initial states of the robot and environment) then jumping to (2.1);

(2.2) According to environmental code I_t, look for match degrees of ζ greater than match antibody set among antibody rule database [A_g], match degree adopting expressions (5) to calculate rightly. Choose the biggest antibody of δ vitality in order to match antibody A_g in this set. If it does not find match antibody then create new antibody automatically with the same environmental code, and write into the antibody database;

(2.3) Roulette algorithm is chosen to match antibody instruction set of A_g, the higher definition instruction the heavier probability to be chosen;

(2.4) Jump (2) after instruction execution;

(3)The genetic algorithm seeks optimal path;

(3.1)Initial colony's individual record of gene;

(3.2)Genetic initial colony quantity check, if quantity doesn't meet the demands, jump to (2.1) after resetting system;

(3.3)The optimum individual keeps the genetic algorithm to seek optimum;

(4) Begin to revise the rule antibody database;

(4.1)Adopt optimum instruction bunch of individual to revise memory rule antibody database, activated vitality δ of antibody increase, non-activated vitality δ of the antibody drops, when δ =0 antibodies die. Calculate formulae of the antibody is (4)

(4.2)Activated antibody instruction definition η_i is modified according to the formulae (3);

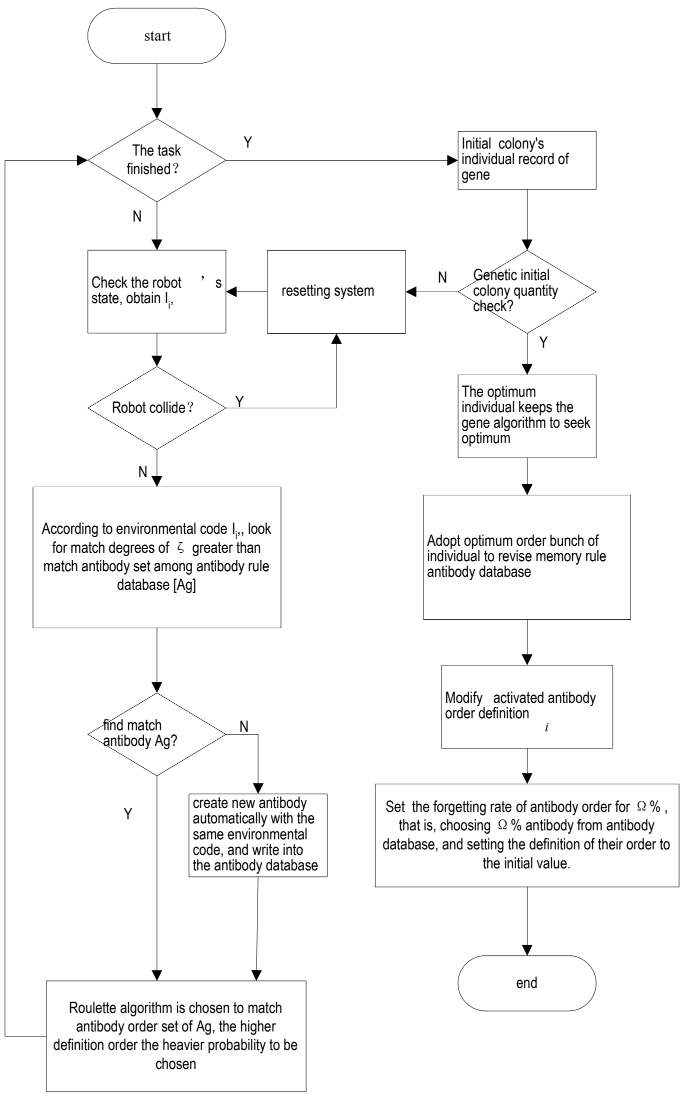


Fig.5 The flow chart of the algorithm.

(4.3)Set up the forgetting rate of antibody instruction for Ω %, that is, choosing Ω% antibody from antibody database, and setting the definition of their instruction to the initial value.

Among this algorithm, roulette algorithm is chosen to the antibody instruction s, already guarantee the rationality of the instruction, guarantee little probability incident possibility, i.e. instruction space can be searched entirely for individual antibody that is to say. The introduction of the genetic algorithm is for the optimum interior diagram of the antibody, because of particularity of robot path planning problem, namely feasible solving space is relatively narrow, but difficult to obtain. The speed of genetic algorithm is fast when it seeks in feasible solution space. Revising regular antibody database is the course of knowledge acquisition. Through revising instruction definition and vitality, the system store knowledge to the antibody. Death of antibody guarantee antibody database to be infinite, guarantee the search tempo of the antibody, certainly its negative effect is the forgetting of knowledge. Settlement the forgetting rate of antibody makes the system dynamic characteristic, guarantees the possibility of antibody instruction space to be searched for further, negative effect is knowledge forgotten.

V. SIMULATION EXPERIMENT

Simulation experiment is MobotSim [1] finish on the computers of PⅣ1.8G, 256M memory. The parameter is: The gene initializes the colony and counts k =20, the establishing value of degree ζ, is 1.0. The forgetting rate Ω is 1%. The experimental result shows in Fig. 6.

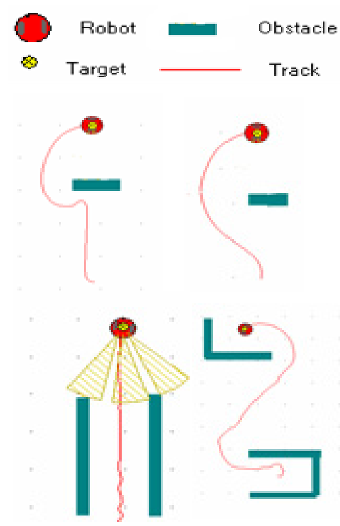


Fig.6. Simulation result

In Fig.6, group (a) is plan to wind for the front barrier, among them a1 for orbit that gene didn't optimizes plan, it is not optimum obviously; a2 for orbit that gene optimizes plan,

[1] http://www.mobotsoft.com

its orbit is rational. Fig. 6 (b) and (c) are the robot orbit planning drawing under the complicated environment.

Above- mentioned three group planning time of experiment smaller than 10 minutes, antibody number in regular antibody database counts to be 184 after the three group experiments.

VI. CONCLUSION

This paper depicts an immunity algorithm for path planning of autonomous mobile robot. Result of the simulation experiment indicates that the algorithm can finish different task required of the robot system within shorter time, and shows the algorithm have fine flexibility and speed. It is obvious the proposed immunity algorithm provides a principled way to planning path of the autonomous mobile robot.

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