Immune Network Algorithm Based on Improved APF for On-Line Dynamic Planning

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***Abstract*—To solve the problem of on-line dynamic planning of mobile robots in unknown environments, inspired by the mechanism of idiotypic network hypothesis, a hybrid immune network algorithm (HINA) is proposed. To improve the planning efficiency of immune network algorithm (INA) and realize optimal on-line dynamic obstacle avoidance, a new adaptive artificial potential field (AAPF) method is presented by using modified potential field. The vaccine is extracted according to the planning results based on AAPF method, and the instruction definition of robot is initialized through vaccine inoculation, which improve the planning efficiency of INA. When the robot meets with moving obstacles during the path planning, the AAPF method is used for the optimal dynamic obstacle avoidance. Simulation results are presented to verify the effectiveness of the proposed algorithm in unknown environments.**

***Keywords*—path planning, artificial potential field, immune network**

I. INTRODUCTION

Dynamic planning is one of the most difficult tasks for autonomous mobile robots in unknown environments, and there are no effective solutions now. Cao et al. [1] used an evolutionary artificial potential field algorithm to solve the dynamic path, but it brings local minimum problem easily. Hu et al. [2] proposed a knowledge based GA for dynamic path planning, but the calculation is bigger and the real-time performance of system is worse.

In recent years, much attention has been focused on the artificial intelligence algorithms. Inspired by the biological immune system, the artificial immune system (AIS) is used gradually in path planning for its properties of self-organization, self-learning and immunological memory. Li et al. [3] presented an immune genetic algorithm for path planning through crossover, mutation and vaccine inoculation operators. Ishiguro et al. [4] [5] designed a behavior controller based on the idiotypic network hypothesis. Luh et al. [6] proposed a reactive immune network and applied it to intelligent mobile robot learning navigation strategies in unknown environments. The available research results based on AIS indicate that the studies mainly focus on the static environments, while few studies have paid attention to the dynamic environments. Wang et al. [7] proposed an obstacle-avoiding planning method based on artificial immune algorithm. The method realized dynamic planning by adding expected direction design and adaptive learning design, however the obstacle-avoiding manner wasn't the optimal, and the robot couldn't actively avoid moving obstacles.

In this paper, a hybrid immune network algorithm is presented to solve the on-line dynamic path planning in unknown environments. To decrease the reliance of immune network on initial condition and realize the optimal dynamic obstacle avoidance, a new adaptive APF method is proposed by building new position and velocity potential field, and used in the following two aspects: first, the vaccine is extracted according to the planning results based on the AAPF, and the INA is initialized through vaccine inoculation; secondly, the AAPF method is used to actively avoid moving obstacles. For the abundance rule database will improve the planning efficiency, our algorithm includes two parts: one is learning algorithm for rule database, the other is on-line dynamic planning algorithm. In this paper, we proceed as follow: Section II provides a description of proposed artificial immune system. Section III gives the basic principle of AAPF. Section IV presents the HINA, including main operators, learning algorithm for rule database, and on-line dynamic planning algorithm. The experiments and analyses are described in Section V. Finally, section VI states some conclusions.

II. ARTIFICIAL IMMUNE SYSTEM

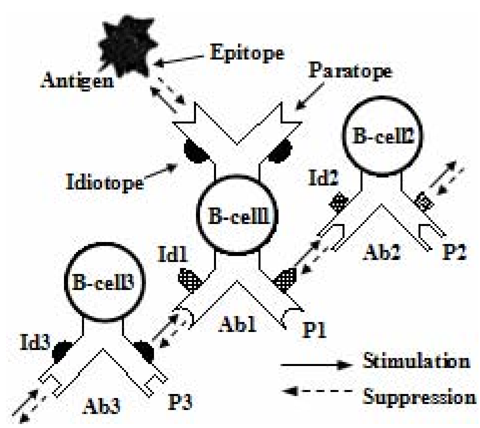

Figure 1. Jerne's idiotypic networks

Biological immune system is a highly complicated system. At present, the commonly accepted theories of immunity are: clonal selection theory of immunity and idiotypic network hypothesis. The latter is proposed by Jerne in 1973 [8] [9]. The idea of Jerne's is schematically shown in Fig. 1. From the figure we can see that the immune network is formed through interaction of 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.

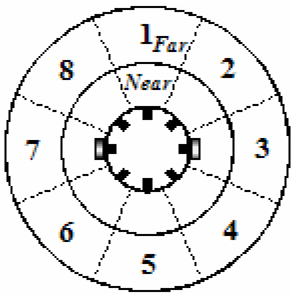

Figure 2. Structure of omni-directional mobile robot

Artificial immune system (AIS) is the simulation of biological immune system (BIS). In the proposed AIS, an omni-directional mobile robot, equipped symmetrically with eight sensors around as shown in Fig. 2, is adopted and regarded as a B lymphocyte (B cell), the sensors coded from 1 to 8 are regarded as the phagocytes, the detecting distance of sensor is divided into two degrees: near and far, the environment surrounding the robot is regarded as antigen, the antigen epitope is the environment coding composed of obstacle information and goal information, the obstacle information is coded according to direction angle and distance, and the goal information is only coded according to direction angle. The antigen *Ag* is defined as follows:

$$Ag = (\chi_{AgO}, \chi_{AgG}) \tag{1}$$

Where, $\chi_{AgO} = \bigcup_{i=1}^{8} AgO_i$ is the code of obstacle information. $\forall\ i = 1,2,\cdots,8$, $AgO_i \in \{00,10,11\}$, the element of the set denotes non-obstacle, near distance and far distance respectively. $\chi_{AgG} = \bigcup_{i=1}^{8} AgG_i$ is the code of goal information , $\forall\ i = 1,2,\cdots,8$, $AgG_i \in \{0,1\}$, the element of the set denotes non-goal and goal respectively.

The action strategy of robot is regarded as antibody. The antibody idiotope is composed of obstacle information χ_{AbO} and goal information χ_{AbG}. They are coded as the antigen is coded. The antibody paratope is the eight moving instruction set *C* of robot. The antibody *Ab* is defined as follows:

$$Ab = (\chi_{AbO}, \chi_{AbG}, C) \tag{2}$$

Where, *C = {a,b,... ,h}*, and the element of the set denotes forward, left forward, right forward, left move, right move, left back, right back, back respectively.

Fig. 3 is the model of path planning based on immune network. The main idea of path planning is: the moving trail of robot is described with a series of antibodies (i.e., antibody network) according to the stimulation and suppression between antigen and antibody. The connection among antibodies is not invariable, and an antibody can reach other antibodies, which depends on the environment surrounding the robot and instruction definition of the robot. In the figure, the thicker the line delegating the definition is, the more correct the instruction is. The essence of path planning is to find an inner figure composed by antibodies, and the figure describing the moving trail of robot is the best.

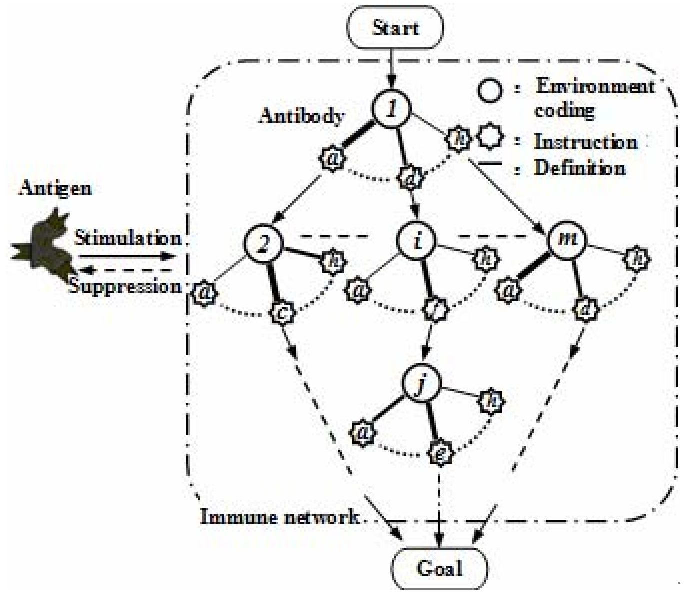

Figure 3. Model of path planning based on immune network

III. ADAPTIVE APF METHOD

APF was proposed by Khatib in 1986[10]. Traditional APF was suitable for the static environment. To solve the avoidance in dynamic environments, a series of improved methods were presented [1] [11] [12], however the planning path has the local wandering, and wasn't smooth. In this paper, we propose a new adaptive APF method based on traditional APF by building new position and velocity potential field. The proposed method solves the active avoidance well. To simplify the analysis, we make the following assumptions:

Assumption 1: The position $p_r(t)$ and velocity $v_r(t)$ of robot at time t are known.

Assumption 2: $p_o(t)$ and $v_o(t)$ are the position and velocity of obstacle at time t , which can be accurately measured on-line.

Assumption 3: The goal is a fixed point in the path whose position p_g is known.

A. *Attractive Potential Function*

For the goal is a fixed point, the attractive potential is defined as a function of the relative distance between the robot and target. The function is presented as follows:

$$U_{att}(p) = \frac{1}{2}\xi\rho^2(p_r, p_g) \tag{3}$$

Where, ξ denotes the scalar positive parameter.

The virtual attractive force is defined as the negative gradient of the attractive potential in terms of position.

$$F_{att}(p) = -\nabla_p U_{att}(p) = -\xi\rho(p_r, p_g)\nabla\rho(p_r, p_g)$$

$$= \xi \rho_{rg} n_{RG} \tag{4}$$

Where $\rho_{rg} = \rho(p_r, p_g)$, n_{RG} is the unit vector pointing from the robot to the goal.

B. Repulsive Potential Function

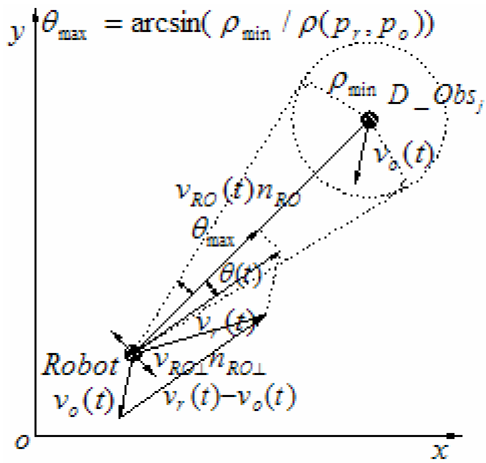

Figure 4. Correlation of position and velocity between the robot and obstacle

The repulsive potential function is constructed according to the single moving obstacle model. Fig. 4 is the correlation of position and velocity between the robot and obstacle. From the figure, we can see that the possibility of collision depends upon two variables: one is the relative position between the robot and obstacle, the other is the relative velocity in the direction from the robot to the obstacle. In this paper, a new repulsive potential function is defined as follows:

$$U_{rep}(p,v) = \begin{cases} [\varphi(\dfrac{1}{\rho(p_r,p_o)-\rho_{\min}} - \dfrac{1}{\rho_0-\rho_{\min}}) & \rho(p_r,p_o) \le \rho_0 \\ +\zeta(\rho(v_r,v_o)\cos\theta)]\rho^2(p_r,p_g) & and \quad \cos\theta > 0 \\ \mathbf{0} & others \end{cases} \tag{5}$$

Where, $\rho(p_r, p_o) = \|p_r(t) - p_o(t)\|$ is the Euclidean distance of relative position between the robot and target, $\rho(v_r, v_o) = \|v_r(t) - v_o(t)\|$ is the Euclidean distance of relative velocity between the robot and target, φ is the scalar positive position parameter, ζ is the scalar positive velocity parameter, ρ_0 is the influence range of obstacle, and $\rho_{\min}$ is the allowable shortest distance between the robot and obstacle.

$$U_{rep}(p,v) = \begin{cases} [\varphi(\dfrac{1}{\rho_{ro}-\rho_{\min}} - \dfrac{1}{\rho_0-\rho_{\min}}) & \rho_{ro} \le \rho_0 \\ +\zeta v_{RO}(t)]\rho_{rg}^2 & and \quad \cos\theta > 0 \\ \mathbf{0} & others \end{cases} \tag{6}$$

Where, $\rho_{ro} = \rho(p_r, p_o)$, $v_{RO}(t) = \rho(v_r, v_o)\cos\theta$.

Similar to the definition of attractive force, the new repulsive force is defined as the negative gradient of the repulsive potential in terms of position.

$$\begin{aligned} F_{rep}(p,v) &= -\nabla_p U_{rep}(p,v) \\ &= [-\varphi \frac{1}{(\rho_{ro}-\rho_{\min})^2} n_{RO} + \zeta(\nabla_p(v_{RO}(t))]\rho_{rg}^2 \\ &+ 2[\varphi(\frac{1}{\rho_{ro}-\rho_{\min}} - \frac{1}{\rho_0-\rho_{\min}}) + \zeta(v_{RO}(t))]\rho_{rg} n_{RG} \end{aligned} \tag{7}$$

Where, n_{RO} is the unit vector pointing from the robot to obstacle.

$$\begin{aligned} \because \nabla_p(v_{RO}(t)) &= \nabla_q(\rho(v_r, v_o)\cos\theta) \\ &= -\frac{v_{RO\perp} n_{RO\perp}}{\rho(p_r, p_o)} \end{aligned} \tag{8}$$

Where , $v_{RO\perp} = \sqrt{\rho(v, v_o)^2 - v_{RO}(t)^2}$;

$\left|n_{RO\perp}^T \times n_{RO}\right| = 1$; $n_{RO\perp}^T n_{RO} = 0$.

Substituting (8) into (7), we have

$$\begin{aligned} F_{rep}(p,v) &= -\nabla_p U_{rep}(p,v) \\ &= F_{rep1} n_{OR} + F_{rep2} n_{RO\perp} + F_{rep3} n_{RG} \end{aligned} \tag{9}$$

Where,

$$F_{rep1} = \varphi \frac{1}{(\rho_{ro}-\rho_{\min})^2} \rho_{rg}^2 \tag{10}$$

$$F_{rep2} = \zeta \frac{v_{RO\perp}}{\rho_{ro}-\rho_{\min}} \rho_{rg}^2 \tag{11}$$

$$F_{rep3} = 2[\varphi(\frac{1}{\rho_{ro}-\rho_{\min}} - \frac{1}{\rho_0-\rho_{\min}}) + \zeta(v_{RO}(t))]\rho_{rg} \tag{12}$$

The force analysis of robot in potential field is shown in Fig. 5.

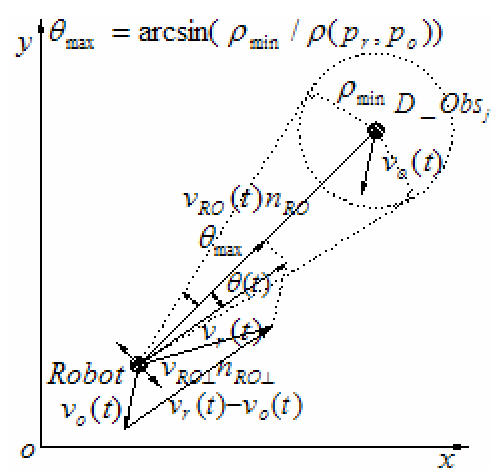

Figure 5. Force analysis of robot in potential field

IV. INA BASED ON AAPF FOR PATH PLANNING

A. Main Operators

1) Antibody / Antigen Affinity Operator

In the HINA for path planning, the environment matching (i.e. the stimulation and suppression between antigen and antibody) is used to search antibodies, and the matching rate is evaluated by affinity of antigen / antibody. The affinity Agb is defined as follows:

$$Agb = \overline{(AgO - AbO)} \bullet \overline{(AgG - AbG)} \qquad (13)$$

2) Instruction Choosing Operator

In the HINA, an antibody can reach other antibodies, and the state transition of antibody depends on the choice probability of instruction. In this paper, the instruction choosing operator is defined as follows:

$$p_i(t) = \frac{\eta_i^{\alpha}(t) q_i^{\beta}(t)}{\sum_{l=1}^{8} \eta_l^{\alpha}(t) q_l^{\beta}(t)} \qquad (14)$$

Where, α is enlightening factor of instruction definition, β is the goal enlightening factor, $\eta_i(t)$ is the instruction definition, and $q_i(t)$ is the goal enlightening function of i th instruction. The $q_i(t)$ is defined as follows:

$$q_i(t) = \frac{1}{\Delta d(i) - \min(\Delta d) + l} \qquad (15)$$

Where, $\Delta d(i)$ is the variation of distance between the robot and goal after the robot transits according to i th ($i \in C$) instruction, l represents the adjusting coefficient, and $l > 0$.

In this paper, the selection of instruction is carried out on a roulette-wheel manner, which not only guarantees the choice feasibility of instruction but also guarantees the possibility of small probability affair.

3) Instruction Definition Operating Operator

In this paper, the definition operating operator includes three parts: the definition encouraging function, definition forgetting function and definition punishing function.

When the robot finishes a search, the definition of executing instructions should be encouraged, and the definition of non-executing instructions should be forgotten. The definition encouraging function is defined as follows:

$$\eta(t) = \eta(t-1) + \mu / L \qquad (16)$$

Where, μ is the encouraging factor, L is the length of feasible path after planning.

The definition forgetting function is defined as follows:

$$\eta(t) = \gamma \cdot \eta(t-1) \qquad (17)$$

Where, γ is the forgetting rate.

At the same time, if the wandering appears during the path planning, the definition of corresponding executing instructions should be punished according to (16), which will provide opportunity to other antibodies in the same environment. In this paper, the strategies of retracing and instruction definition punishing are proposed. The detailed operations are as follows:

First, the robot retraces N_b steps until the front obstacles are far away or there are no obstacles in front of robot from the point of wandering, then the corresponding instruction definitions are punished. The instruction definition punishing function is defined as follows:

$$\eta^m(t) = \eta^m(t-1) * (1 - 1/m) \qquad (18)$$

Here, m $(1 \le m \le N_b)$ is the retracing step.

4) Vaccine Extraction and Inoculation Operator

If there is no any prior knowledge, the initial instruction definition of new antibody is $\eta_i = 1/N$ (N is the number of instruction of an antibody), namely the choice probability of each instruction is equal. To avoid absolute random transition of the robot and improve the searching efficiency of immune network, the planning results based on AAPF are taken as prior knowledge, and the initial instruction definition of new antibody is initialized through vaccine extraction and inoculation. The concrete operating sequences are as follows:

Step 1 Confirm a new antibody.

Step 2 Calculate the attractive force and repulsive force of the robot based on AAPF method.

Step 3 Calculate the deflexion direction of the robot according to the resultant virtual force.

Step 4 Calculate the angers between deflexion direction and all moving directions of instructions.

Step 5 The instruction with minimal anger is given the maximal instruction definition, then the instruction is taken as center, and other instructions are given the definition symmetrically with equal weights.

In our experiment, according to the increasing sequence of angers, the initial definitions of eight instructions are given {0.4， 0.2， 0.2， 0.08， 0.08， 0.015， 0.015， 0.01} respectively.

B. Learning Algorithm for Rule Database

Step 1 Choose learning examples and initialize parameters: $\xi, \varphi, \zeta, \rho_0, \rho_{\min}, \alpha, \beta, l\ \mu, \gamma$.

Step 2 Recognize antigen and judge whether the robot wanders. If not, go to Step 4.

Step 3 Carry out the strategies of retracing and instruction definition punishing, update the rule database, and go to Step 2.

Step 4 Look for a matching antibody according to (13) in rule database. If exists, go to Step 6.

Step 5 Produce a new antibody according to the antigen, finish vaccine extraction and inoculation, and write in rule database.

Step 6 Choose a instruction which won't result in collision according to (14) (15) from the matching antibody or new antibody.

Step 7 Execute the chosen instruction.

Step 8 Judge whether the robot reaches the goal. If not, go to Step 2.

Step 9 Update the antibodies in rule database according to (16) (17), and end.

C. On-Line Dynamic Planning Algorithm

Step 1 Initiate the task.

Step 2 Obtain environmental information of robot, and judge whether there are moving objects within the influence range of obstacle. If there is none, go to Step 4.

Step 3 Execute the optimal dynamic avoidance by applying AAPF method, and go to Step 2.

Step 4 Look for the matching antibody in the rule database according to the antigen. If exists, go to Step 6.

Step 5 Produce a new antibody according to the environment, finish the vaccine extraction and inoculation, and write it in rule database.

Step 6 Choose a instruction, whose definition is the most and which won't result in collision, from the matching antibody or new antibody.

Step 7 Execute the chosen instruction and judge whether the robot wanders. If so, the strategies of retracing and instruction definition punishing are carried out and the rule database is updated, otherwise, go to the next step.

Step 8 Judge whether the robot reaches the goal. If not, go to Step 2, otherwise update rule database and end.

V. SIMULATION RESULTS AND ANALYSIS

To confirm the validity of our proposed method in section IV, two experiments are carried out as follows:

A. Learning Experiments for Rule Database

For the abundance rule database will improve the planning efficiency, we carry out a series of learning experiments to achieve rules in different environments. The parameters of algorithm are: $\xi = 50$, $\varphi = 1$, $\zeta = 15$, $\rho_0 = 4m$, $\rho_{\min} = 0.2m$, $\alpha = 2$, $\beta = 2$, $l = 0.01$, $\mu = 5$, $\gamma = 0.1$, Fig. 6 is the simulation of six typical learning environments. The robot learns 30 times in each environment. In the figure, the lines with symbol "●" denote all feasible antibody networks, the line with "■" denotes the best path. From the figure, we can see that the robot has the properties of self-learning, self-organization and find the way in all kinds of complicated environments. Through the above learning, the robot will achieve abundant rules, which will improve the on-line planning efficiency.

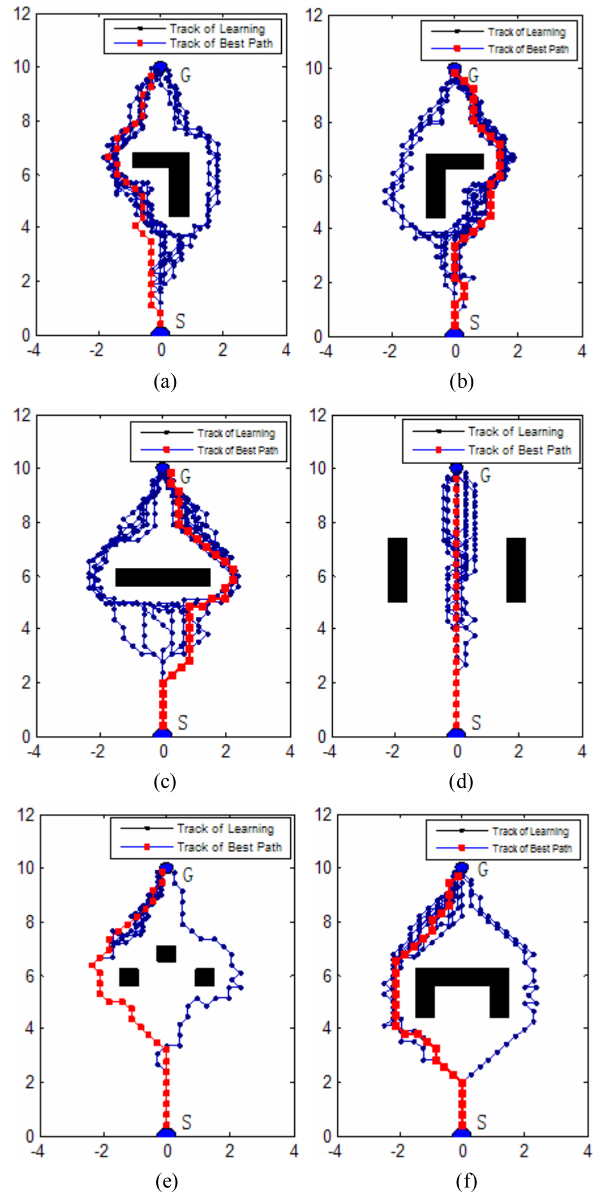

Figure 6. Simulation of six typical learning environments

B. On-Line Dynamic Planning

To show the effectiveness of INA based on AAPF in dynamic environments, we have the dynamic obstacle-avoiding experiment with MATLAB7.0 on an Intel Pentium IV 2.99GHz computer with 512MB RAM. The simulation environment is shown in Fig. 7 where there are two dynamic obstacles and several static obstacles including concave obstacle. The partial parameters of environment are shown in TABLE I.

TABLE I. PARTIAL PARAMETERS OF ENVIRONMENT

Parameters	**Robot**	**Dynamic Obstacles**		**Goal**
		D_obs1	*D_obs2*	
start Time (s)	0	7	7	0
initial Position (m)	$[0,4]^T$	$[6.4,6.8]^T$	$[6.4,1.2]^T$	$[20,4]^T$
velocity (m/s)	$[0.4,0]^T$	$[-0.40,0.55]^T$	$[-0.05,-0.29]^T$	$[0,0]^T$

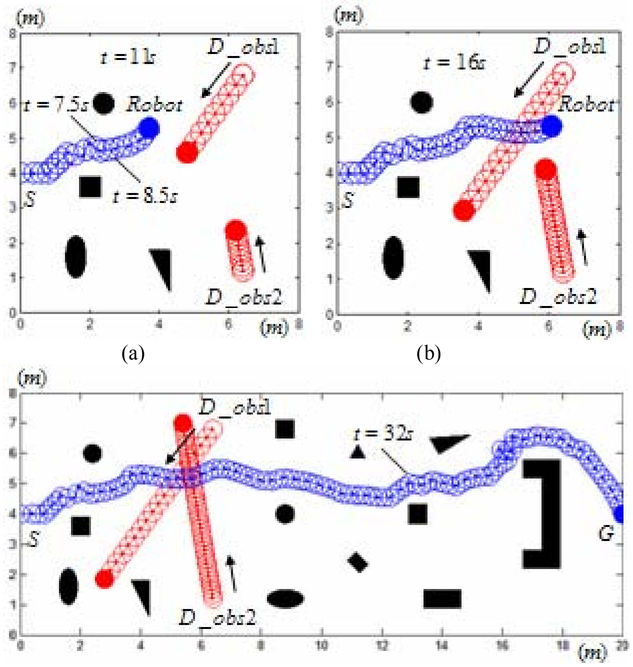

Figure 7. Simulation of path planning in a dynamic environment: (a) t = 11s; (b) t = 16s; (c) the whole path planning

At first, the robot sets off from point $[0, 4]^T$ and executes on-line dynamic planning by getting matching antibody or vaccine extraction and inoculation. When the robot enters the influence of D_obs1 and D_obs2 at $t = 7.5s$ and $t = 8.5s$ respectively, it executes the optimal dynamic obstacle-avoiding planning by applying AAPF method. For the obstacle D_obs1 is much faster than the robot, the robot actively detours the D_obs1 from its back according to the relative position and velocity between them. Fig. 7 (a) is the obstacle-avoiding state at $t = 11s$. As to the obstacle D_obs2, the robot actively detours it from its front as shown in Fig. 7(b). Fig. 7(a) and (b) clearly show how the robot quickly avoids two moving obstacles with the optimal manner. When the robot escapes from the influence range of moving obstacles, it plans the path again according to the matching between antigen and antibody or the vaccine extraction and inoculation. When the robot enters the influence of concave obstacle at t=32s, it escapes the local minimum successfully through the immunological memory and matching between the antigen and antibody, and reaches the goal finally. The whole path planning is shown in Fig. 7(c).

TABLE II. CONTRAST OF DYNAMIC PLANNING AMONG THREE ALGORITHMS

Methods / Planning Performance	HINA	INA	GA
calculation time by computer (s)	0.97	1.23	12.13
length of optimal path (m)	23.60	25.12	23.25

TABLE II is the contrast of dynamic planning among three algorithms (i.e., HINA, INA [7] and GA [2]). The main parameters of INA are the same as in [7]. The population size of GA is 20, crossover probability is 0.8, and mutation probability is 0.1. From the table, we can see that the calculation time of GA is longer than HINA and INA for its large calculation, the time of HINA is the shortest for its high convergence based on vaccine extraction and inoculation. The planning length of GA is the shortest for its global search. The length of INA is the longest for the robot can't choose the optimal avoidance manner to avoid the moving obstacles. The length of HINA is shorter than INA for active obstacle avoidance based on AAPF. All in all, the proposed HINA based on AAPF has the better performance than other two methods.

VI. CONCLUSIONS

Inspired by the mechanism of idiotypic network hypothesis, a novel immune network algorithm based on AAPF method is presented to solve the on-line dynamic path planning in unknown environments. According to the simulation experiments, we can draw the following conclusions: (1) The adaptive APF method is an effective method, which is useful for the initialization of INA and optimal dynamic avoidance; (2) The characteristics, such as stimulation and suppression between antigen and antibody, vaccine extraction and inoculation, immunological memory, etc. solve the on-line dynamic planning well in unknown environments.

ACKNOWLEDGMENT

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