Dynamic Mobile Robot Navigation Using Potential Field Based Immune Network

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ABSTRACT

This paper proposes a potential filed immune network (PFIN) for dynamic navigation of mobile robots in an unknown environment with moving obstacles and fixed/moving targets. The Velocity Obstacle method is utilized to determine imminent obstacle collision of a robot moving in the time-varying environment. The response of the overall immune network is derived by the aid of fuzzy system. Simulation results are presented to verify the effectiveness of the proposed methodology in unknown environments with single and multiple moving obstacles.

Keywords: dynamic navigation, potential field immune network, Velocity Obstacle method, moving obstacle

1. 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. In addition, their capabilities also allow them to carry out specialized tasks in hazardous or hardly accessible environments for human beings such as nuclear plants and chemical handling. They are also useful in emergencies for fire extinguishing and rescue operations. Combined with manipulation abilities, their capabilities and efficiency will increase and can be used for dangerous tasks such as security guard, exposition processing, as well as undersea, underground and even space exploration.

In order to adapt the robot's behavior to any complex, and dynamic environment without further human intervention, it should be able to extract information from the environment, to perceive, and act within the environment. An autonomous robot must be able to maneuver effectively in its environment, achieving its goals while avoiding collisions with static and dynamic obstacles. As a result, motion planning of a mobile robot plays an important role in robotics and has thus attracted the attention of researchers recently. Various methods have been proposed for this purpose, such as configuration-time space based method [1-2], planning in space and time independently [3], Artificial potential fields based approach [4-8], cooperative collision avoidance and navigation [9-10], fuzzy based method [11], velocity obstacles method [12-17], and collision cone approach [18-20].

In motion planning problems of mobile robots, motion behaviors of the mobile robot can be classified into two fundamental behaviors: obstacle-avoidance and goal-seeking. An important approach is the well-known potential field method first introduced by Khatib [21]. The basic idea is to fill the robot's workspace with an artificial potential field and the robot moves in a direction along the resultant of a repulsive force from the obstacle and an attractive force towards the goal. This method is particularly attractive since it is conceptually effective and easy to implement. However, most of the previous studies use it to deal with mobile robot path planning in stationary environments where targets and obstacles were all stationary. In an effort to solve the problem of motion planning in a dynamic environment, Conn and Kam [4] included time as one of the dimensions and thus the moving obstacles can be regarded as stationary in the extended world. The major problem in this approach is that the trajectories of the moving obstacles are assumed known a priori, which are often inapplicable in real applications. Then, Vadakkepat *et al*. [5] proposed a new methodology named Evolutionary Artificial Potential Field (EAPF) to solve moving-obstacle problem. Genetic algorithm was employed to derive optimal potential field functions. In addition, an escape-force algorithm was introduced to avoid the local minima associated with EAPF. Later, Ge and Cui [6] proposed a new potential field method for motion planning of a mobile robot in a dynamic environment. The new potential functions take into account not only the relative positions of the robot with respect to the target and obstacles, but also the relative velocities of the robot with respect to the target and obstacles. Then, Poty [7] merged the approach proposed in [6] and the fractional potential for dynamic motion planning of mobile robot. The fractional potential was utilized to characterize danger zone and risk coefficient of each obstacle. Computer simulations demonstrated that mobile robot avoided obstacles and reached the target successfully. Recently, Munasinghe *et al*. [8] proposed the velocity dipole field and its integration with the conventional potential field to form a new real-time obstacle avoidance algorithm. Unlike the radial field lines of conventional potential field, the velocity dipole field has elliptical field lines that navigate a robot more skillfully. It is useful to skillfully guide the robot around obstacles, quite similar to the way humans avoid moving obstacles.

Another approach is the Velocity Obstacle (VO) method first proposed by Fiorini and Shiller [12-13]. The Velocity Obstacle paradigm is a well-known collision detection method. Moving obstacles are mapped into a two-dimensional "velocity space". Then velocity of mobile robot is directly planned using the

Velocity Obstacle in this space. The velocity obstacle is a first-order approximation of the robot's velocities that would cause a collision with an obstacle at some future time, within a given time horizon. With this representation, an obstacle maneuver can be computed simply by selecting velocities outside of the velocity obstacle. A complete trajectory is constructed by the sequence of all the avoidance maneuvers performed by the mobile robot. The trajectory is generated in real-time by selecting a single avoidance velocity at each time interval, using some heuristics to choose among all possible velocities in the reachable avoidance velocity set. Three strategies namely the Towards Goal strategy, the Maximum Velocity strategy, and the Structure heuristics were presented in [14]. Later, VO has been extended in [15] for obstacles moving on arbitrary (but known) trajectories and applied for on-line navigation of the robotic wheelchair [15-16].

A similar and VO related approach based on the Collision Cone is presented in [18] for motion planning. It was illustrated that the Collision Cone can effectively determine if collision between a robot and an obstacle is imminent. In addition, No restrictions were placed on the shapes of the robot or obstacle, *i.e.*, they can both be of any arbitrary shape.

This paper proposes a potential filed immune network (PFIN) for dynamic motion planning of mobile robots in an unknown environment with moving obstacles and fixed/moving target. In addition, the Velocity Obstacle method is employed to determine potential collisions of a robot moving in the time-varying environment. It has been shown that the learning and adaptive capabilities of artificial immune systems have a great potential in the fields of machine learning, computer science and engineering [22-24]. Dasgupta [22] summarized that the immune system has the following features: self-organizing, memory, recognition, adaptation, and learning. There are a growing number 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. In our previous study [25], it has demonstrated that an autonomous robot is able to maneuver effectively in its environment, achieving its goals while avoiding collisions with static obstacles and escaping from the local minimum.

2. BIOLOGICAL IMMUNE SYSTEM

The immune system protects living bodies from the invading of foreign substances, called antigens, including viruses, bacteria, and other parasites. Lymphocytes float freely in blood and lymph nodes, and patrol everywhere for antigens, then gradually drift back into the lymphatic system, to begin the cycle all over again [26]. There are mainly two types of lymphocytes, namely B-cells and T-cells, which play an important role in immunities. The former takes part in the humoral immunity that secretes antibodies (Abs) by clonal proliferation, and the latter takes part in cell mediated immunity. One class of T-cells, called Killer T-cell, destroys the infected cell whenever they recognize the infection. The other class which trigger clonal expansion and stimulate/suppress antibody formation is called Helper T-cell. The APC (Antigen Presenting Cell) interprets the antigen appendage and extracts the features, by processing and presenting antigenic peptides on its surface to T-cell and B-cell. Fig. 1 depicts the model describing the relationship between components in the immune system.

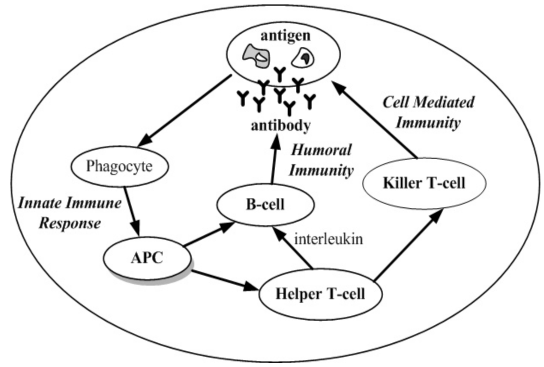


Fig. 1 Illustration of the biological immune system

When an infectious foreign pathogen attacks the human body, the macrophage has surface receptors to detect and destroy the invader. Then the macrophage 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 T-cell and B-cell. These antigenic peptides are kinds of molecules called MHC (Major Histocompatibility Complex) to distinguish a "self" from other "non-self" (antigen). These lymphocytes will be capable to sensitize this antigen and be activated. Then the Helper T-cell releases the interleukines which are the stimulation or suppression signals acting on the cells. In the other hand, B-cell becomes stimulated when an antibody receptor binds to an antigen. Moreover, B-cells are also affected by Helper T-cells during the immune responses. The Helper T-cell plays a remarkable key role for deciding the immune system toward the cell mediated immunity or the humoral immunity, and connects the non-specific immune response to make a more efficiency specific immune response.

Affinity maturation occurs when the maturation rate of a B-cell clone increases in response to a match between the clone's antibody and an antigen. Subsequently, those mutant cells are bound more tightly and stimulated to divide more rapidly. Affinity maturation dynamically balances exploration versus exploitation in adaptive immunity. 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. In addition, the immunity can be maintained even faced with a dynamically changing environment. The biological immune system can recognize different pathogen patterns and generate selective immune responses. Recognition is achieved by inter-cellular binding, which is determined by molecule shape and electrostatic charge. Hence, B-cell becomes stimulated when an antibody receptor binds to an antigen. Antibodies have the capability of binding pathogens that they have never learned to recognize. This kind of anticipatory capability is due to a broad coverage of pathogen space realized by the antibody receptors produced by the immune system [27].

An artificial immune system can be defined as abstract computational system for solving complex computational or engineering problems. The concepts of the artificial immune system are inspired by ideas, processes, and components, which extracted from the immune system. It has also been shown that the learning capability of artificial immune systems has a great potential in the field of machine learning, computer science and engineering. Jerne [28] has proposed the idiotypic network hypothesis (immune network hypothesis) based on mutual stimulus and suppression between antibodies shown in Fig. 2. This hypothesis is modeled as a differential equation simulating the concentration of a set of lymphocytes. The concept of immune network states that the network dynamically maintains the memory using a feedback mechanism within the network. Jerne concluded that the immune system is similar to the nervous system when viewed as a functional network. Based on Jerne's immune network hypothesis, several theories and mathematical models for immune system have been developed.

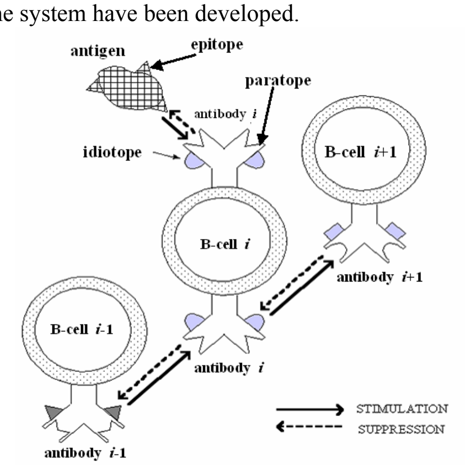


Fig. 2 Idiotypic network hypothesis

Hightower *et al.* [29] suggested that all possible antigens could be declared as a group of set points in an antigen space and antigen molecules with similar shapes occupy neighboring points in that space. It indicates that an antibody molecule can recognize some set of antigens and consequently covers some portion of antigen space as Fig. 3 illustrated. The collective immune response of the immune network is represented as

$$\sum_{i=1}^{N_{Ab}} f(Ab_i)$$

where $f(Ab_i)$ indicates the immune response function between antigen and the *i*th antibody. Note that any antigen in the overlapping converge could be recognized by several different antibodies simultaneously. Afterward, Timmis *et al*. [30] introduced similar concept named Artificial Recognition Ball (ARB). Each ARB represents a certain number of B-cells or resources, and total number of resources of system is limited. In addition, each ARB describes a multi-dimensional data item that could be matched to an antigen or to another ARB in the network by Euclidean distance. Those ARBs located in the other's influence regions would either be merged to limit the population growth or pulled away to explore new area. ARBs are essentially a compression mechanism that takes the B-cells to a higher granularity level.

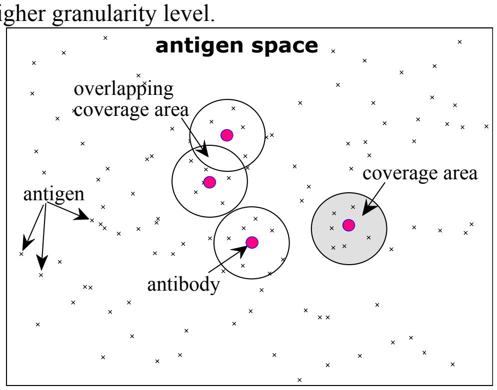


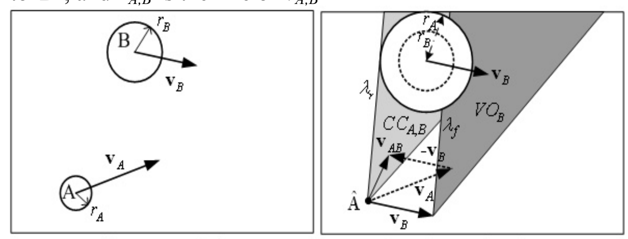
Fig.3 The antigen space

3. THE VELOCITY OBSTACLE

This section describes the velocity obstacle (VO) for single and multiple obstacles. For simplicity, the mobile robot and moving obstacles are assumed to be approximated by cylinders and move on a flat floor. Fig. 4(*a*) shows two circular objects A and B with velocities $\mathbf{v}_A$ and $\mathbf{v}_B$ at time t_0, respectively. Let circle A represent the robot and circle B represent the obstacle. To compute the VO, obstacle B must be mapped into the configuration space of A, by reducing A to a point $\hat{A}$ and enlarging B by the radius of A to $\hat{B}$ as Fig. 4(*b*) demonstrates. The Collision Cone, $CC_{A,B}$, is thus defined as the set of colliding relative velocities between $\hat{A}$ and $\hat{B}$.

$$CC_{A,B} = \left\{ \mathbf{v}_{A,B} \mid \lambda_{A,B} \cap \hat{B} \neq \emptyset \right\}$$

where $\mathbf{v}_{A,B} = \mathbf{v}_A - \mathbf{v}_B$ is the relatively velocity of $\hat{A}$ with respect to $\hat{B}$, and $\lambda_{A,B}$ is the line of $\mathbf{v}_{A,B}$



(*a*) two objects on collision course (b) velocity obstacle VO

Fig. 4 The Velocity Obstacle approac

This collision cone is the light gray sector with apex in $\hat{A}$, bounded by the two tangents λ_f and λ_r from $\hat{A}$ to $\hat{B}$ as shown in Fig. 4(*b*). Clearly, any relative velocity $\mathbf{v}_{A,B}$ outside $CC_{A,B}$ is guaranteed to be collision-free, provided that the obstacle $\hat{B}$ maintains its current shape and speed. The collision cone is specific to a particular robot/obstacle pair. To consider situation of multiple obstacles, it is better to establish an equivalent condition on the absolute velocities $\mathbf{v}_A$. This could be done simply by adding the velocity $\mathbf{v}_B$ to each velocity in $CC_{A,B}$, or equivalently, translating the collision cone $CC_{A,B}$ by $\mathbf{v}_B$, as shown in Figure 4(*b*). The velocity obstacle VO (in dark gray sector) is thus defined as:

$$VO = CC_{A,B} \oplus \mathbf{v}_{A,B}$$

where $\oplus$ is the Minkowski vector sum operator. The VO partitions the absolute velocities $\mathbf{v}_A$ into avoiding and colliding velocities. Selecting $\mathbf{v}_A$ outside of VO would avoid collision with B. Velocities $\mathbf{v}_A$ on the boundaries of VO would result in A grazing B.

In the case of multiple obstacles, they are prioritized according to their danger level so that the most imminent collision obstacle is avoided first in this paper. A "collision distance index" is defined as follows to compute the danger level for each obstacle

$$\delta = \frac{d_{r,obs_j}}{v_j \times T_s}, \quad j = 1,2,\cdots,N_{obs}$$

where d_{r,obs_j} represents the distance between robot and the *j*th obstacle, v_j is the speed of the *j*th obstacle, T_s is the sampling time used in simulations.

4. POTENTIAL FIELD IMMUNE NETWORK

A potential field based immune network (PFIN) inspired by the biological immune system for robot navigation (goal-reaching and obstacle-avoidance) in dynamic environment is described in this section. For simplicity, one can make the following choices without loss of any generality.

• The mobile robot is an omni-directional vehicle. This means any direction of velocity can be produced at any time. In addition, maximum velocity and acceleration are assumed to be limited considering dynamics of robot and obstacle.

• The mobile robot and moving obstacles under consideration are approximated by cylinder with radius r_r, and r_o. This is not a severe limitation since general polygons can be represented by a collection of circles [18, 31, 32]. Chazelle [31] showed that the union of all these circles can still be meaningfully used to predict collision between the irregularly shaped objects. Moreover, the resulting inexact collision cone can still be used effectively for motion planning.

• The mobile robot and moving obstacles move in a flat floor. Moving obstacles may changes their velocities (amplitude and direction) at any time.

• The obstacles move along arbitrary trajectories, and that their instantaneous state (position and velocity) is either known or measurable. Prassler *et al.* have proposed such a sensor system which has a laser range finder and sonar [15].

Fig. 5 illustrates the architecture of the proposed potential field based immune network for mobile robot navigation in dynamic environment. The proposed mechanism, imitating the cooperation between B-T cells, can help the robot adapt to the environment efficiently. In the immunology, the T-cell plays a remarkable key role for distinguishing a "self" from other "non-self" antigens. Resembling the biological immune system, its function is to prioritize the obstacles employing the VO method so that the obstacle with most imminent collision can be identified. In other words, T-cell in PFIN distinguishes an "imminent" from other "far-away" obstacles.

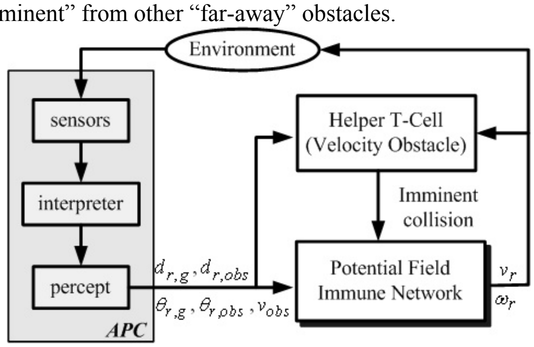


Fig. 5 The architecture of the potential field immune networK

In PFIN, the antigen's epitope is a situation detected by sensors and provides the information about the relationship between the robot's current states and the obstacles, along with the target (*i.e.* $d_{r,g}$, $\theta_{r,g}$, d_{r,obs_j}, θ_{r,obs_j}, v_{obs_j}) as Fig. 5 depicted. This scene-based spatial relationship is consistently discriminative between different parts of an environment. The interpreter is regarded as a phagocyte and translates sensor data into perception. The antigen presentation proceeds from the information extraction to the perception translation. An antigen may have several different epitopes, which means that an antigen can be recognized by a number of different antibodies. However, an antibody can bind only one antigen's epitope.

In this study, the antigen represents the local environment surrounding the robot each time interval and its epitopes are a fusion data set for each obstacle as Fig. 6 shows

$$Ag_j \equiv \{\theta_{r,g}, d_{r,g}, \theta_{r,obs_j}, d_{r,obs_j}\} \qquad j = 1, 2, \cdots, N_{obs}$$

where $\theta_{r,g}$ and θ_{r,obs_j} represent the orientations between robot and target, the *j*th obstacle, respectively. $d_{r,g}$ and d_{r,obs_j} are the distance between robot and target, the *j*th obstacle, respectively. N_{obs} is the number of moving obstacles. This scene-based spatial relationship is consistently discriminative between different parts of an environment. The interpreter is regarded as a phagocyte and translates sensor data into perception. The antigen presentation proceeds from the information extraction to the perception translation. An antigen may have several different epitopes, which means that an antigen can be recognized by a number of different antibodies. However, an antibody can bind only one antigen's epitope.

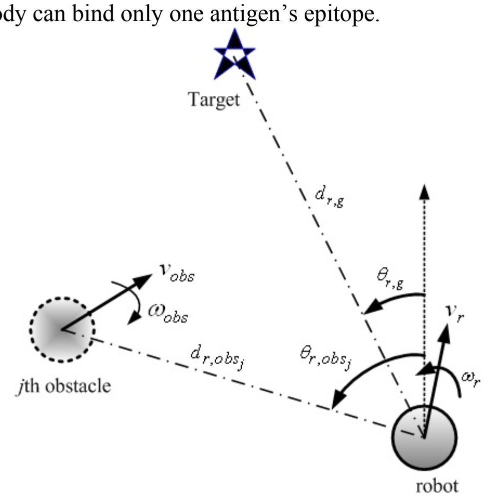


Fig. 6 Configuration of mobile robot, obstacles, and target

In the proposed immune network, the antibody's receptor is defined as the situation between robot and the imminent collision obstacle: $Ab_1 = d_{r,g}$; $Ab_2 = \theta_{r,g}$; $Ab_3 = d_{r,obs}$; $Ab_4 = \theta_{r,obs}$, where $d_{r,obs}$ and $\theta_{r,obs}$ represent the distance and orientation between the robot and obstacles.

The response of the overall immune network is derived by determining the set of affinities associated with the receptors and the structural similarity between antigen and antibody defined by quantification of the distance in antigen space. In this study, the collective immune response function of the immune network is represented as the following function,

$$\begin{cases} v_r = f(Ab_1) + f(Ab_3) \\ \omega_r = f(Ab_2) + f(Ab_4) \end{cases}$$

where v_r and ω_r are the robot's velocity and angular velocity outputs, respectively. This is a kind of artificial potential field approach since it considers a virtual attractive force between the robot and the target (*i.e.* $f(Ab_1)$ and $f(Ab_2)$) as well as virtual repulsive forces between the robot and the obstacles (*i.e.* $f(Ab_3)$ and $f(Ab_4)$). The resultant force on the robot is then used to decide the velocities (*i.e.* v_r and ω_r) of its movements. Functions $f(Ab_i)$ are expressed as following,

$$f(Ab_i) = K_i \times \frac{\sum_{j=1}^{4} m_i \times m_{ij}}{\sum_{j=1}^{4} m_{ij}}, \quad i = 1, 2, 3, 4$$

where m_i is the affinity of antigen (the most imminent collision obstacle) and the *i*th antibody, m_{ij} is the affinity between the *i*th and *j*th antibody. Corresponding constant parameters are K_1= 20, K_2= 30, K_3= 15, K_4= 20, respectively. The affinity of the antigen and the *i*th antibody m_i is fuzzified using the fuzzy set definitions as Fig. 7 illustrates. The mapping from the fuzzy subspace to the TSK model is represented as fuzzy if-then rules,

IF $d_{r,g}$ is *zero* THEN v_r = 0cm/s
IF $d_{r,g}$ is *near* THEN v_r = 10cm/s
IF $d_{r,g}$ is *medium* THEN v_r = 15cm/s
IF $d_{r,g}$ is *far* THEN v_r = 20cm/s
IF $\theta_{r,g}$ is *-far* THEN ω_r = -30º/s
IF $\theta_{r,g}$ is *-medium* THEN ω_r = -25º/s
IF $\theta_{r,g}$ is *-near* THEN ω_r = -20º/s
IF $\theta_{r,g}$ is *-close* THEN ω_r = -10º/s
IF $\theta_{r,g}$ is *+close* THEN ω_r = 10º/s
IF $\theta_{r,g}$ is *+near* THEN ω_r = 20º/s
IF $\theta_{r,g}$ is *+medium* THEN ω_r = 25º/s
IF $\theta_{r,g}$ is *+far* THEN ω_r = 30 º/s
IF $d_{r,obs}$ is *zero* THEN v_r= -15cm/s
IF $d_{r,obs}$ is *near* THEN v_r= -10cm/s
IF $d_{r,obs}$ is *medium* THEN v_r = -5cm/s
IF $d_{r,obs}$ is *far* THEN v_r = 0cm/s
IF $\theta_{r,obs}$ is *-far* THEN ω_r = 10º/s
IF $\theta_{r,obs}$ is *-medium* THEN ω_r = 20º/s
IF $\theta_{r,obs}$ is *-near* THEN ω_r = 30º/s
IF $\theta_{r,obs}$ is *+near* THEN ω_r = -30º/s
IF $\theta_{r,obs}$ is *+medium* THEN ω_r = -20º/s
IF $\theta_{r,obs}$ is *+far* THEN ω_r = -10º/s

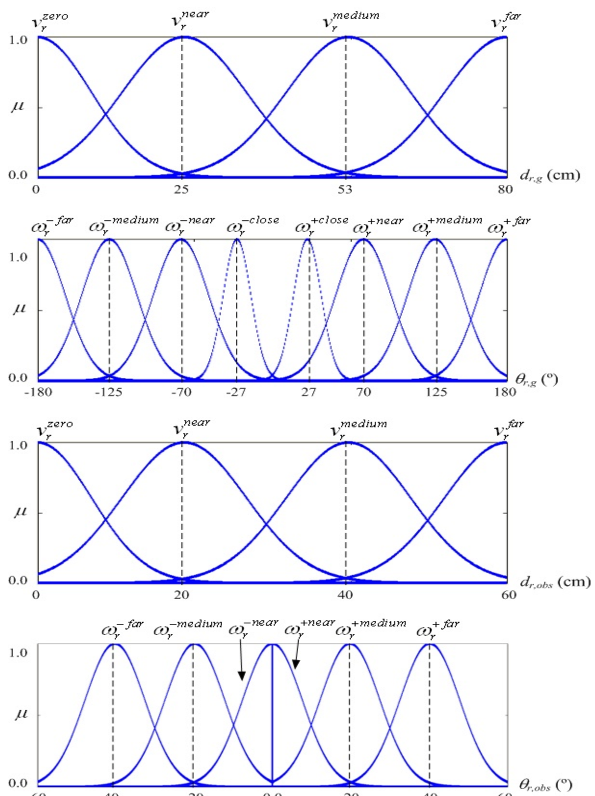


Fig. 7 Membership functions of antibodies

Consequently, the centroid defuzzification method is employed to calculate the weighted average of a fuzzy set.

$$m_i = \frac{\sum_{k=0}^{L} \mu_k y_k}{\sum_{k=0}^{L} \mu_k}, \quad i = 1, 2, 3, 4$$

where μ_k represent the matching degree of the kth rule and y_k represent its corresponding output value.
Finally, the stimulation and suppressive interaction between the ith and jth antibodies m_{ij} are listed in Table 1. It should be noted that these value are optimized utilizing genetic algorithms. Hundreds of different circumstances with randomly generated moving obstacles were employed to optimize the affinity values m_{ij} of PFIN. Fig. 8 demonstrates one of the cases in which several tens of obstacles circumrotate at randomly generated positions with different radius. Fig. 8(*a*) shows that robot reaches target successfully while Fig. 8(*b*) demonstrates that robot is failed to reach target in the optimization procedure.

Table 1 Optimized affinity values between antibodies

m_{ij}	j=1	j=2	j=3	j=4
i=1	1	-0.13	-0.24	-0.04
i=2	-0.02	1	-0.11	-0.42
i=3	-0.37	-0.84	1	0.92
i=4	-0.21	-0.92	-0.31	1

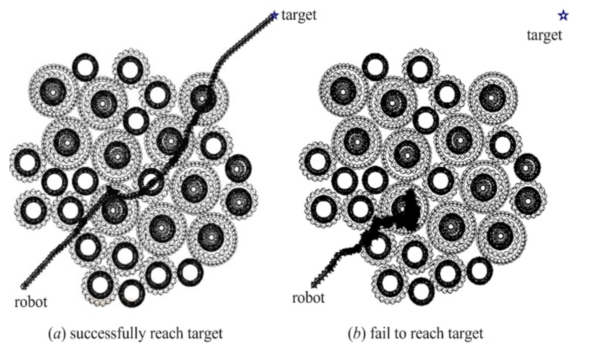


Fig. 8 Randomly generated moving obstacles for optimizing m_{ij}

5. SIMULATIONS AND DISCUSSION

Numerous simulations have been performed to evaluate the performance and effectiveness of a mobile robot among multiple moving obstacles using the proposed PFIN. In the simulation, the size of the test field is 5m ×5m, and the radius of robot and obstacles are r_r = 0.1 m and r_o = 0.1 m. In addition, the constraints on mobile robot and moving obstacles are $v_{r\,\max}$ = 20 cm/s, $v_{o\,\max}$ = 20 and $\omega_{r\,\max}$ = 30º/s. The sampling time for each step is T_s = 0.03sec. To carry out these computations, a computer program was developed with C++ programming tools with a graphical user interface. Fig. 9 illustrates the example of a simulation window for motion planning of mobile robot among two moving obstacles, including windows of the setting parameters, and trajectories for robot and obstacles.

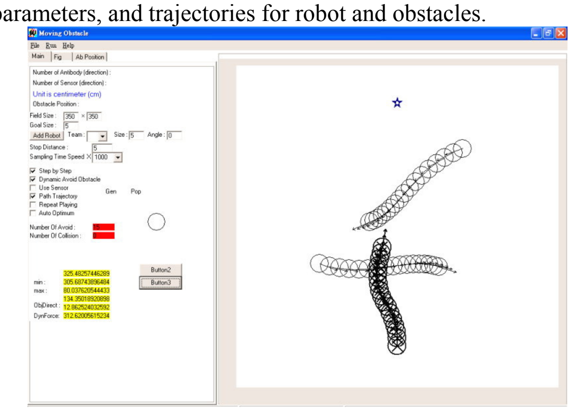


Fig. 9 Simulation window for mobile robot motion planning in dynamic environment

The simulation examples demonstrated in Figs. 10–14 are given with graphical representations in which the trajectories of the moving object and the robot are described. Moreover, figures show the velocity-time history and azimuth-time history of the robot, respectively. In each figure, circles indicate the position of the robot and obstacles at each time instant when the robot executed an action. A high concentration of circles indicates a lower velocity (of the obstacle and of the robot) whilst a low concentration is a reflection of a greater velocity. In addition, the state responses (speed and orientation) of robot and obstacles are depicted in the figures. Obviously, the robot smoothly avoids the moving obstacles and reaches goal as expected for all cases.

Fig. 10 reveals that an obstacle coming from left side along a straight line cross the robot path. Within the interval of points A and B (at twelfth and seventh sampling instant respectively), the obstacle slows down its speed in front of the robot's way to goal. Clearly, the robot is unable to pass the obstacle before it. Therefore, the robot turn left and decelerates its speed quickly to avoid it. At the seventh sampling instant, the robot turns right slightly and then passed over behind the obstacle since the obstacle is no longer a threat. Finally, the robot turns right quickly and accelerates to reach the goal safely.

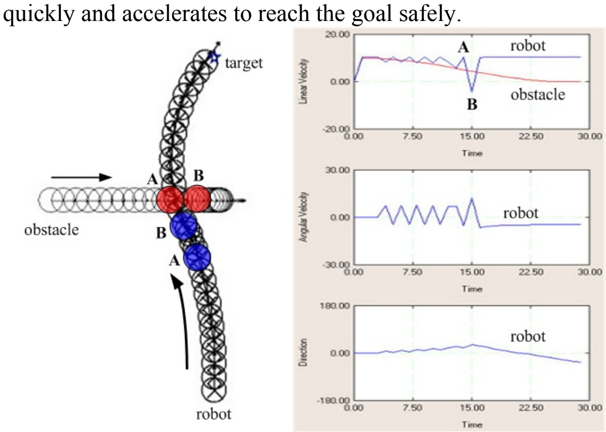


Fig. 10 Trajectories of mobile robot and obstacle

Fig. 11 shows a simulation result by which the robot can avoid the two moving obstacles one after another then reach the goal. These obstacles come from different sides with arbitrary trajectory and varying speed cross the robot path. Similar to the previous simulation, the robot decelerates its speed at points A and B to avoid the first and second obstacles separately. Then it accelerates and moves towards the goal without collision.

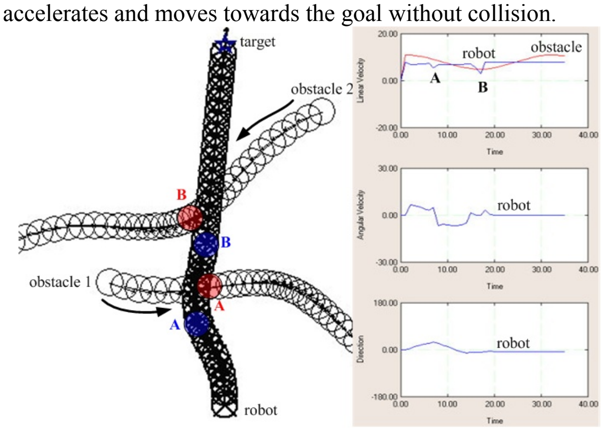


Fig. 11 Trajectories of mobile robot and two obstacles

Consider the case when the robot, the obstacle and the target move in the same direction along the same line and the obstacle is in between, as shown in Fig. 12. To solve this kind of local minimum problem described in [6], the simplest method is to keep the robot moves and wait for the obstacles or the target to change their motion. However, if the situation is still unchanged and the robot still trapped after a certain period's waiting, Ge and Cui [6] suggested applying the conventional local minimum recovery approaches designed for the stationary environment cases. Fig. 12 demonstrates that the proposed PFIN is capable of solving this problem without extra approach. Mobile robot tries to pass the obstacle and escape from the trap situation by adjusting its speed and direction at point B and C. Finally, it exceeds the obstacle and reaches the goal safely after point D.

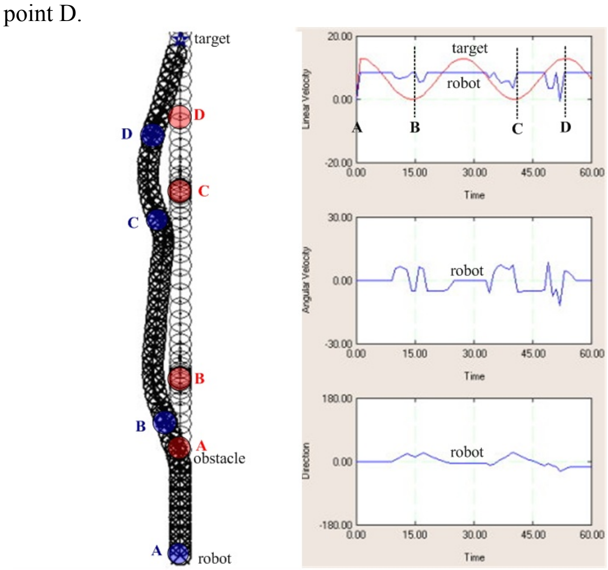


Fig. 12 Trajectories of mobile robot and obstacle

Fig. 13 demonstrates the motion planning of a mobile robot tracking a moving goal while avoiding two moving obstacles. Obviously, mobile robot is able to reach goal and avoid moving obstacles no matter what the goal is fixed or moving employing the proposed PFIN. Note that the two obstacles have the same trajectories in both cases.

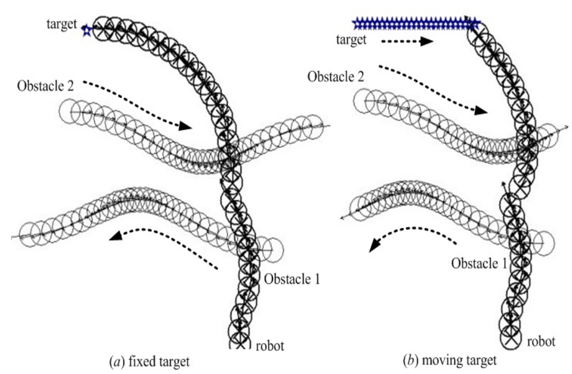


Fig. 13 Trajectories for fixed and moving goal

Fig. 14 demonstrates another example of motion planning for the case of suddenly moving/stopped obstacle. Figs. 14(*a*) – 14(*d*) illustrate a simulation result by which the robot successfully avoid two moving and two static obstacles. As usual, the robot exceeds the first moving obstacle at position A' and waits for the second moving obstacle at position C'. Fig. 14(*e*) demonstrates that the robot reaches target safely even though the second static obstacle abruptly moves when the robot approaches it. Fig. 14(*f*) shows the similar result except that the second moving obstacle unexpectedly stops when it near the robot. Clearly, the proposed potential filed immune network can avoide moving anf stationary obstacles effectively and efficiently.

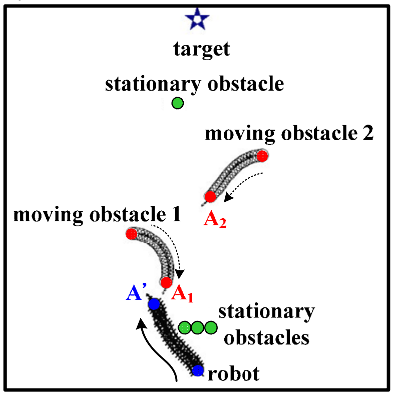


Fig. 14(*a*)

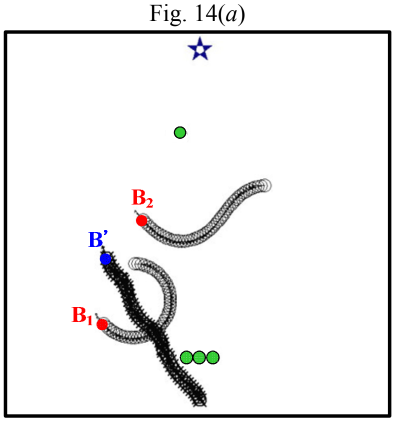


Fig. 14(*b*)

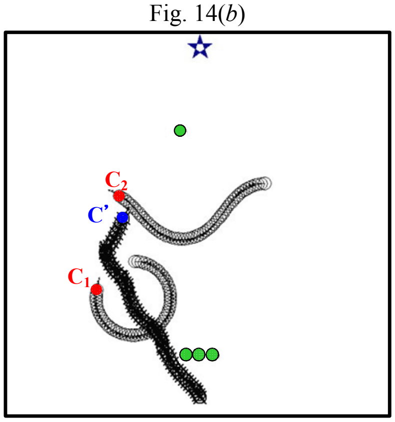


Fig. 14(*c*)

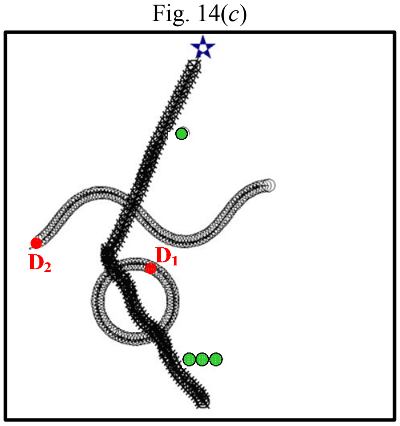


Fig. 14(*d*)

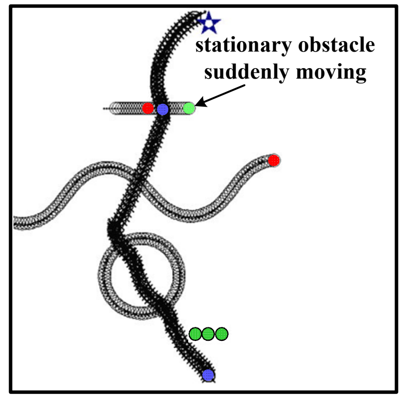


Fig. 14(*e*)

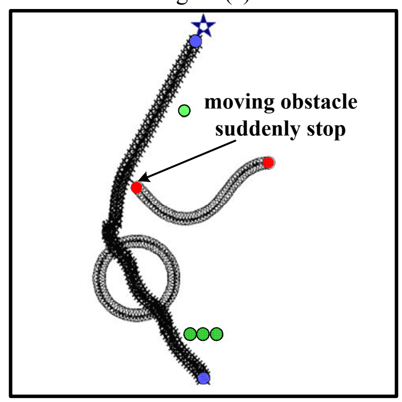


Fig. 14(*f*)

Fig. 14 Trajectories of robot and obstacles for suddenly moving/stopped obstacle

6. CONCLUSIONS

In this paper, a novel potential field immune network has been proposed for mobile robot motion planning in a dynamic environment in which the target and obstacles may be moving at the same time. The moving obstacles approaching the robot are not subjected to any restriction in its movements. They can vary their velocities and directions at any moment.
Velocity obstacle method was adopted to determine the imminent obstacle whereas the immune network was utilized to avoid obstacle and reach goal. Simulation results validate the performance and effectiveness of the proposed methods.

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