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Path Planning of Mobile Robot Based on Improved Artificial Immune Algorithm

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Abstract: The path planning of robot is a very complex problem, not only to find a shortest path without collision, but also requires the path as smooth as possible and meet certain safety. This paper first introduces the hardware structure and the software platform of robot soccer, and focus on the transformation of power system, then, introduces the traditional algorithm for robot path planning and intelligent planning algorithm, on the basis of the above work analyzed the advantages and disadvantages of the present various path programming method, thus put forward a kind of path planning of mobile robot improved artificial immune algorithm. According to the static path planning, spatial model is set up using the grid method, and the initial path populations need build artificial immune algorithm using artificial potential field method, the optimization of the mutation operator, puts forward new function of affinity, and the introduction of vaccination, crossover and mutation and other immune mechanism, which can generate good individuals earlier, thus ensuring the convergence rate of the algorithm and the diversity of population, prevent premature convergence, improves the global search ability. The simulation results show that, the method has good adaptability in a static environment, can effectively guarantee the quality and improve the efficiency of path planning and path planning.

Keywords: Path planning, potential field immune, soccer Robots, affinity fitness function.

1. INTRODUCTION

With the development of computer technology, sensor technology and micro electronics technology, the open mobile robot platform constantly developed, the research of mobile robot emerged a new climax. Subsequently, 80 appeared in the intelligence system, information integration and fusion" and other new terms in science and technology, people begin to research new mobile robot with perception, thinking, decision making and action ability [1]. Especially since 90, with high intelligent mobile robot developed in adaptability, good robustness for the mark, to carry out a higher level, more challenging research work. From the whole process of development, the research of robot is moving more functional, intelligent, popular in the direction of the development [2]. The emerging of soccer robot, intelligent bionic robot, volume of nano robot, tiny dauntless exploration robot, machine NPC family constantly enriched, which more and the proportion of intelligent mobile robots, the larger [3, 4]. It is in such as sports, military, medical treatment is more and more widely in the field will play an important role [5-8].

Path planning is an important part in the research of mobile robots, the robot according to the requirements of instruction and environment information independently determine path, avoid obstacles, to realize the goal of task. Path planning is a guarantee for mobile robot to complete a task, but also an important symbol of intelligent mobile robot degree [9]. Especially in the precision of the robot hardware system in the short term is not effectively improve the situation, the research on the path planning algorithm is particularly important, this will change the navigation performance of the mobile robot to fundamentally improve the level of intelligence, mobile robot, and the moving speed and flexibility, reduce the uncertain state of existence of mobile robot moving in in the process of robot development, transported for a long distance, high intelligent detection and lay the foundation for automatic driving system of robot, robot, car service [10, 11].

In the aspect of the theory of artificial immune system, such as the use of nonlinear chaos theory, mechanism of artificial immune system, immune computation principle, research in this area is still relatively small [12]. Although the artificial immune has aroused widespread interest in many different areas of research personnel, according to the objective questions and research use, researchers have designed many excellent performance of artificial immune algorithm based on immune function of the system, but the existing artificial immune algorithms still exist many defects: such as poor versatility, premature convergence to local optimal solution. These problems mainly lie in the antibody evaluation form, antibody concentration, antibody for the promotion and inhibition and memory use [13]. Combined with the artificial potential field algorithm is this topic to improve the random initial population of antibodies during the artificial immune algorithm, and antibody evaluation form, improve the global searching ability of immune algorithm, and used for mobile robot path planning.

Table 1. Immune algorithm terms correspond with the immune system.

Natural Immune System	Artificial Immune Algorithm	Natural Immune System
Antigen	Optimal Solution	Antigen
Antibody	By seeking to be a solution of the problem	Antibody
From memory cells produce antibodies	Enable optimal solution before	From memory cells produce antibodies
Lymphocyte regeneration	Generate high affinity antibodies	Lymphocyte regeneration
Lymphocyte differentiation	Solutions to maintain excellent	Lymphocyte differentiation

2. RELATED THEORY

2.1. Research Status of Artificial Immune System

1) immune evolutionary algorithm, Fogel, Owens, Walsh from aspects of the principles and concepts of the theory of evolution, the success of the immune algorithm is applied to the field of Engineering Science, unlike other algorithms, immune algorithm research mainly concentrated in the Gauss mutation basis, the main step of the algorithm steps are first determined the accuracy of solutions according to the requirements, then using prior knowledge extraction vaccine, and the calculation of the current parent population of all the individual fitness function, then the current parent populations mutation operation to generate progeny populations, then the subgeneration population vaccinated got new population. The shortcomings of the algorithm is the vaccine to obtain the very strong randomness and with other intelligent algorithms to complementary fusion [14, 15].

2) immune clonal algorithm, the algorithm based on antibody clonal selection mechanism, the clonal selection operator, is the first concrete steps of antibody population initialization, calculation of initial population affinity, on the basis of affinity and setting the antibody clone size, the cloning operation, immune gene operation and clonal selection operation, obtain new antibody population, finally, calculate the antibody population new affinity [16].

3) artificial immune network algorithm, Cook and Hunt on learning and memory ability based on biological immune system, artificial immune network algorithm for machine learning is proposed, the algorithm tries to simulate biological system. Timmis based on Cook and Hunt research, proposed a resource limited artificial immune system, and based on B cell function simulation, constructed artificial immune system function in a similar. On the basis of summarizing forefathers, Castro constructed an artificial immune network algorithm, the algorithm simulates the process of immune network antigenic stimulus, mainly including the antibody and antigen recognition, immune clonal proliferation, affinity maturation and network suppression [17].

Artificial immune system has been applied to the optimization design (such as: TSP problem), network security, fault diagnosis, pattern recognition, image recognition, wide field of machine learning and automatic control, but the immune algorithm is used to study the do path planning of mobile robot is still relatively rare, especially the immune algorithm is applied to the dynamic path planning the environment for mobile robot is more rare.

2.2. The Traditional Path Planning Algorithm

(1) Free Space Approach

Application of free space method for mobile robot path planning, using predefined generalized cone and convex polygon and other basic shape structure of free space, and the free space is represented as a connected graph connectivity, through the search for path planning. This method will be reduced to the point of the robot, the obstacle and the boundary of the surrounding proportionally enlarged, so that the robot can move to any point in the obstacle space, without collision with obstacles. The algorithm is flexible, the starting point and goal point change will not cause the reconstruction of connected graphs, but directly proportional to the complexity and obstacles algorithm, not under any circumstances, can obtain the shortest path.

(2) The artificial potential field method

The artificial potential field method is currently the most research and application of domestic and foreign scholars method. The method is simple, small amount of calculation, the obstacle avoidance and path planning is also taken into account the motion performance of the robot. The artificial potential field method is first proposed by Dr. Khatib in 1986. The basic idea is the artificial potential field structure of the target position of gravitational field and around obstacles repulsive field interaction, through the direction of descent search potential function to find a collision free path, which is the origin of the potential field method.

3. ARTIFICIAL IMMUNE ALGORITHM

Artificial immune theory and biology immune theory, immune operator is divided into two types: full immunity target immunity, respectively corresponding to the biology of the nonspecific and specific immunity, was shown in Table **1**.

3.1. The Main Operator of Artificial Immune Algorithm

Antibody concentration (den (x):S [0, 1]) to characterize the diversity of antibody population quality, antibody

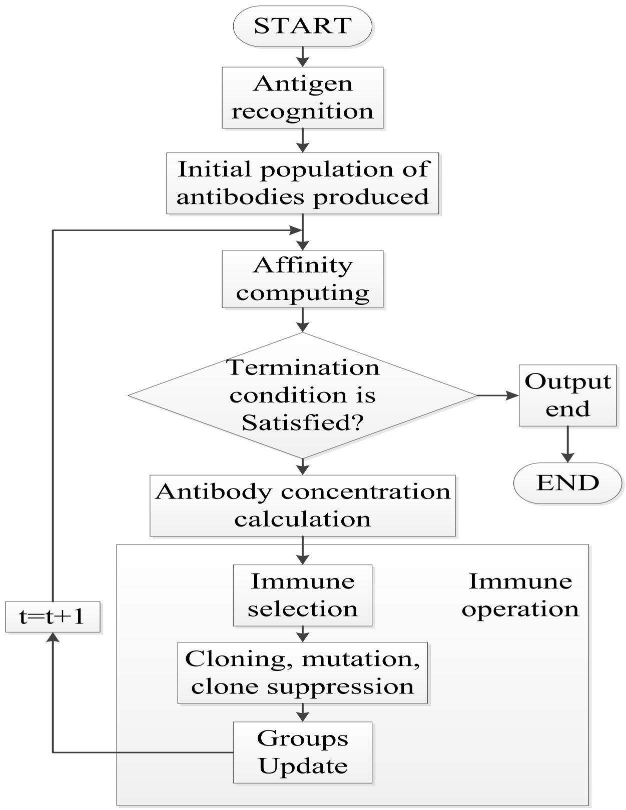

Fig. (1). The program flow chart of artificial immune algorithm.

concentration is too high means the existence of a large number of very similar individuals in a population, then the search will be concentrated in a region of the feasible region, is not conducive to global optimization. Therefore, the optimization of high concentration of individual coping suppression algorithm, ensure the diversity of individual.

$$den(ab_i) = \frac{1}{N}\sum_{j=0}^{N-1} aff(ab_i, ab_j) \quad (1)$$

Calculation of stimulation of antibody usually can use the antibody results for mathematical calculations obtained affinity and concentration of antibody evaluation, as follows:

$$\sin(ab_i) = a \cdot aff(ab_i) - b \cdot den(ab_i) \quad (2)$$

Immune selection operator (Ts: S->S) select which antibodies into the clonal selection operation according to the stimulation of antibody. In the antibody group, individual high quality incentive antibody has better, more likely to be selected for clonal selection operation, in order to search region more in the search space expansion of local search value.

$$T_i(ab_i) = \begin{cases} 1, sim(ab_i) \geq T \\ 0, sim(ab_i) < T \end{cases} \quad (3)$$

3.2. Process of Artificial Immune Algorithm

The program flow chart of artificial immune algorithm was shown in Fig. (**1**).

Artificial immune algorithm implementation steps are as follows:

Step1: The algorithm first antigen recognition, namely understanding to optimization problem, extraction of prior knowledge, generate a random population.

Step2: The definition of affinity evaluation function, in population every feasible solution fitness function evaluation

Step3: To determine whether the meets the conditions for the termination of the algorithm, if the condition is satisfied, then terminate the algorithm optimization process, the output results; otherwise, continue optimizing operation.

Step4: computing antibody concentration.

Step5: immune treatment, including immune selection, clone, mutation and clone inhibition.

(1) According to the population of antibody affinity and concentration calculation results to choose the high quality antibody, make its activation.

(2) Clone copy on the activation of antibodies, and obtains some copy.

(3) Mutation operation to copy was cloned, which make affinity mutation.

(4) The mutation results are then select, inhibition of low affinity antibodies, affinity with the variation of high retention.

Step6 update the population, with a new randomly generated population antibody instead of low affinity antibodies, developed a new generation of antibodies, transgenic Step2.

3.3. Convergence Analysis of Algorithm

Set the population size are N, and all the individuals of the population are m hexadecimal code of n bits. Algorithm of all approximate solution as a point of the state space in S1, and intermediate groups all approximate solution as a point of the state space in S2. When there is no need to distinguish between S1 and S2, you can use the S state space representation. Si said the S in the I state, Vni represents a random variable V in the state of Si in the n generation. Let f (.) is the objective function to be optimized, its domain can be defined for I, f (at) the global optimal solution set:

$$S = \left\{ x \in I \mid f(x) = \max_{x_i \in i} f(x_i) \right\} \quad (4)$$

Proof: Set

$$S_i = (x^0, x^1, ..., x^{N-1}) \in S^1 \quad (5)$$

Let

$$f(s_i) = (f(x^0), f(x^1), ..., f(x^{N-1})) \quad (6)$$

If $f(s_i) = f(s_j)$ or the first component of $(f(s_i) - f(s_j))$ is positive ,then let $s_i \geq s_j$

Furthermore $\beta = \left\{ i \mid s_i \geq s_j, \forall s_j \in S^1 \right\}$, we can know from all above reasons, if $i \in \beta$,then

$S_i = (x^0, x^1, ..., x^{N-1})$ can meet the follow formula:

$$f(x^0) = f(x^1) = ... = f(x^{N-1}) = f^* \tag{7}$$

In the formula, f^* is the global extremum of the objective function to be optimized.

From formula (7), we can know: $s_i \cap S \neq \varnothing$.

Assuming $p_{ij}(n)$ is the transition probabilities of random processes (X_n) , then

$$p_{ij}(n) = p\left\{X'_{n+1} / X'_n\right\} = \sum_{s_i \in s^2} p\left\{C'_n / X'_n\right\} p\left\{X'_{n+1} / X'_n C'_n\right\} \tag{8}$$

Here we discuss two special cases of $p_{ij}(n)$.

when $i \in \beta, j \notin \beta$,for any random i,

$$p\left\{X'_{n+1} / X'_n C'_n\right\} = \sum_{s_i \in s^2} p\left\{C'_n / X'_n B^b_n\right\} p\left\{X'_{n+1} / X'_n B^b_n C'_n\right\} \tag{9}$$

Suppose there is a class of sample data sets:

$$(x_1, y_1), (x_2, y_2), \cdots (x_l, y_l), y_i \in \{-1, 1\} \tag{10}$$

To implement the nonlinear transformation $Z = \phi(x)$ for the sample data x_l

$$\begin{cases} w^T z_i + b \geq 1, y_i = 1 \\ w^T z_i + b \leq -1, y_i = -1 \end{cases} \tag{11}$$

where w represents the weight vector and b is offset vector.

Transform the above equation to obtain:

$$y_i(w^T z_i + b) \geq 1 \quad i = 1, 2, \cdots l \tag{12}$$

Assume the optimal classification plane equation is expressed as

$$w_0^T z + b_0 = 0 \tag{13}$$

Classifier interval

$$\rho(w, b) = \min_{\{x|y=1\}} \frac{z^T w}{\|w\|} - \max_{\{x|y=-1\}} \frac{z^T w}{\|w\|} \tag{14}$$

w_0 must meet

$$\rho(w_0, b_0) = \frac{2}{\|w_0\|} = \frac{2}{\|w_0^T w_0\|} \tag{15}$$

To obtain the maximum, the general quadratic programming is used to solve the optimization problem:

$$\max_{w,b} \phi(w) = \frac{1}{2}(w^T w) \tag{16}$$

4. EXPERIMENTAL RESULTS

4.1. Static Path Planning of Mobile Robot

Path planning in complex static environment, to make the mobile robot from the starting point, around obstacles and reach the target point. The optimal path generally refers to the shortest path length. The main influence factors of mobile robot path planning time is too long code length, code length will influence the running speed of the system, so the first grid method is used simple encoding technique, the equivalent free space model of mobile robot into two-dimensional structured grid model, to identify the grid using a serial number method.

Rectangular coordinate method was shown in Fig. (**2**), in the upper left corner of the grid graph as the origin of coordinates, horizontal to the right as the positive direction of axis X, vertical to the Y axis is the direction, each grid interval for a unit corresponding to the axis length. Any grid can use Cartesian coordinates (x, y) uniquely identifies. X axis represents the length of the site, Y axis represents the width of the pitch.

The relationship between the transformation given above two kinds of representation methods:

$$N = X + 10Y \tag{17}$$

$$\begin{cases} X = \text{mod}(N, 10) \\ Y = \text{int}(N, 10) \end{cases} \tag{18}$$

mod said the remainder from N/10, int represents an integer from N/10.

4.2. Grid Obstacle Classification

Using a two-dimensional Cartesian matrix grid to represent visual sensor to detect the environment map, two-dimensional array to record the environment map corresponding to whether there are obstacles in information grid. Assume that the grid is divided into grids and grid barrier free two classes in each grid cell, given the prior probability conditions, sampling time according to the situation given to occupy the vision sensor grid. If a unit grid with obstacles were observed on the grid, array should be set in world coordinates, through the obstacle raster geometry position to a polar coordinate form of cluster analysis, so that the two-dimensional search process into a one-dimensional search process was shown in Fig. (**3**).

4.3. The Simulation Experiment

In order to validate the artificial immune potential field algorithm is correct and practical, the use of Visual C++ and Matlab7.1 Windows platform in the preparation of a simulation program based on. As shown in Fig. (**4**), where a mobile robot in simulation map VC to do with the square represents

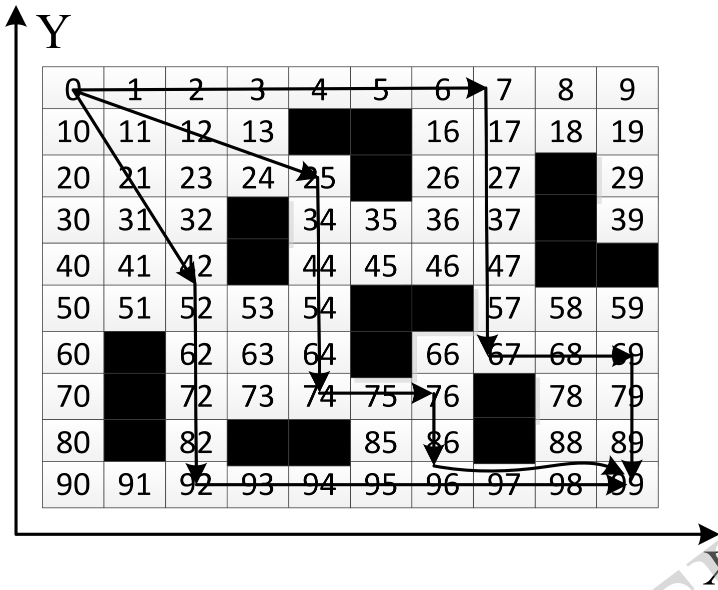

Fig. (2). Rectangular coordinate method.

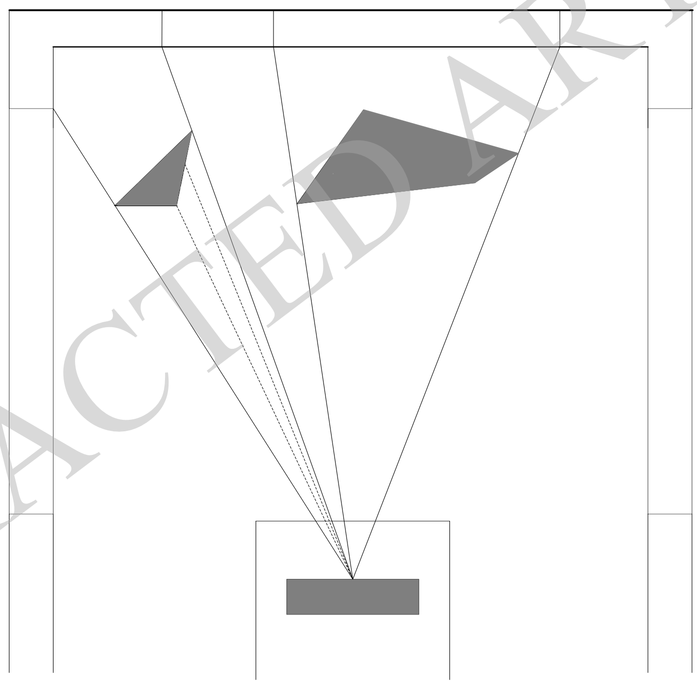

Fig. (3). The two-dimensional search process into a one-dimensional search process.

the search target, namely initial posture; the circle represents the termination of mobile robot pose; the rounded rectangle represents the group of obstacles; black lines for mobile robot path planning of the number of obstacles in the environment.

The upper left to lower right for starting point, end point, based on the immune potential field algorithm and immune algorithm each running 30 times. The two algorithms can find the optimal path of the respective. In view of the complex environment, immune potential field algorithm fully utilizes the initial group sequence, immune operator model, mobile robot to avoid obstacles by antibody selection, finally arrived at the termination of the pose, so that better reflects the robust immune potential field algorithm. In Fig. (**4b**) can further see, for obstacle avoidance using artificial immune potential field algorithm, can make the mobile robot takes much shorter distance and time to reach the destination, the optimal path and immune algorithm standard planning out it using standard immune algorithm, path plan is too long.

To verify the fitness function by using the established MATLAB, as you can see from Fig. (**5**) when the number of iterations is close to 30 times, the use of artificial immune

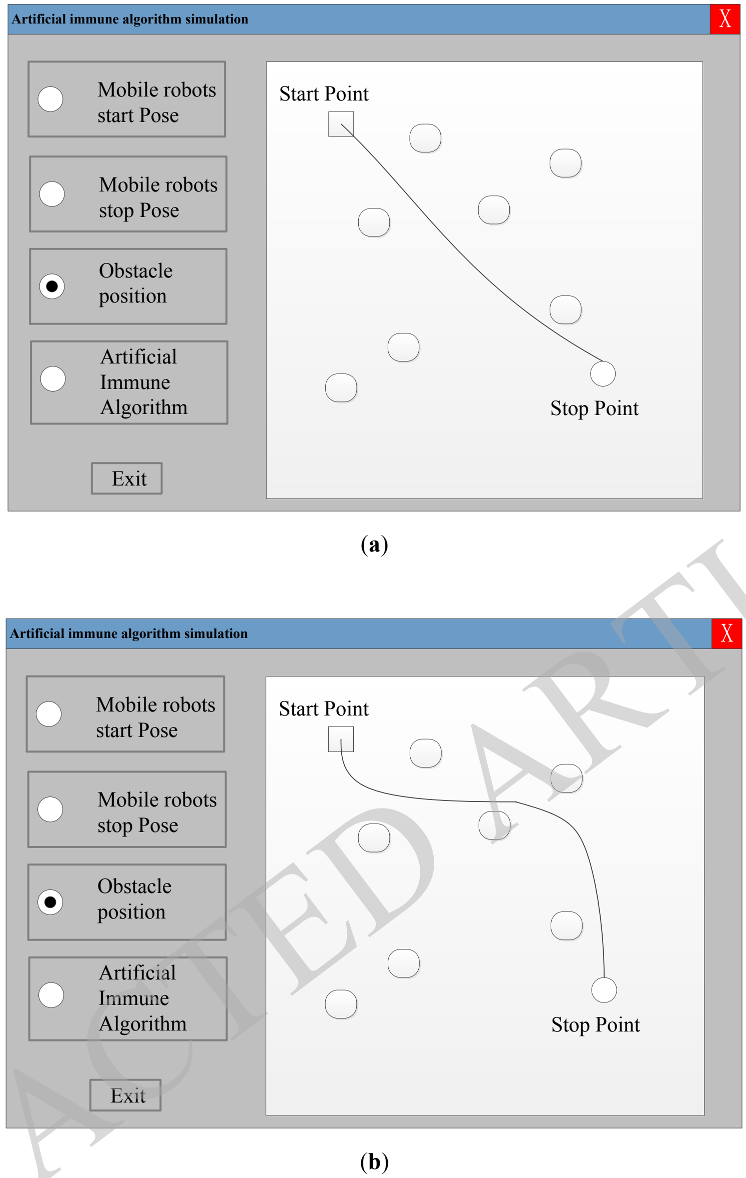

Fig. (4). A mobile robot in simulation map VC with the square.

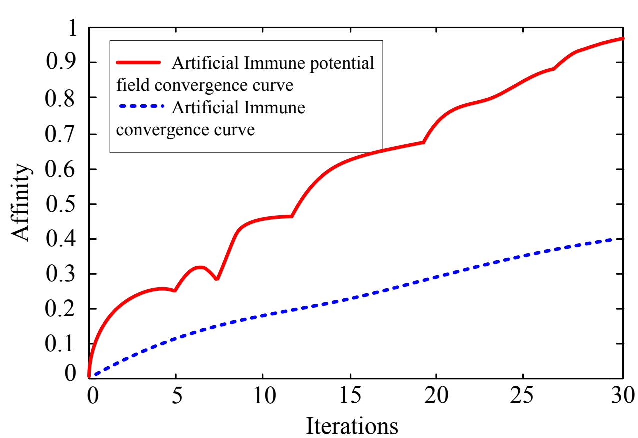

Fig. (5). The number of iterations is close to 30 times.

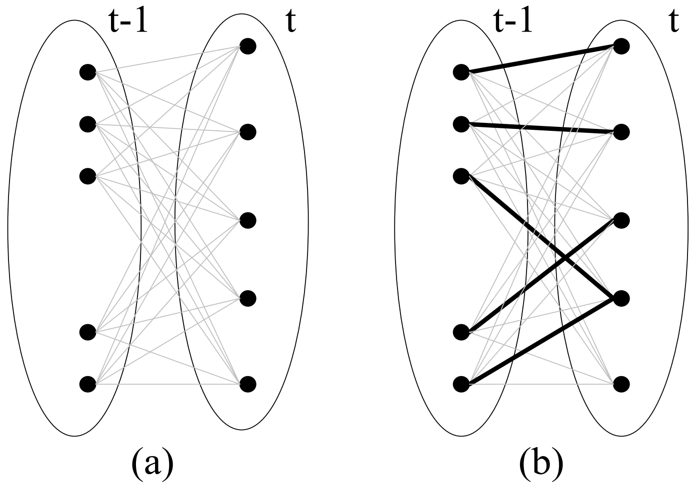

Fig. (6). Tracking is designed in the corresponding relationship between one-to-one correspondence.

potential field algorithm, affinity is close to 1, while the use of artificial immune algorithm in common, when the number of iterations is close to 30 times, the affinity function value is about 0.4, thus we can see that the use of artificial immune potential field algorithm when the number of iterations is close to 30 times, can converge to the global optimal solution, the convergence speed of its convergence speed is faster than the artificial immune algorithm.

For each object in the T-1 time, the deterministic in some sports constraints define it with the t moment an object corresponding to the cost function. Tracking is designed in the corresponding relationship between all Fig. (**6**) to get a one-to-one correspondence between the (Fig. **6b**), there are usually makes the corresponding value of the cost function method for solving minimum Hungary algorithm and greedy search algorithm.

CONCLUSION

Mobile robot to senior stage, intelligent stage, path planning of mobile robot has become a primary issue, in the intelligent mobile robot, path planning is directly related to the level of intelligent mobile robot. At present, the intelligent algorithm is applied to path planning is an important direction of development. An improved immune algorithm proposed in this paper, a new algorithm is improved the randomness of the basic immune algorithm initial population, and the use of some of the characteristics of biological immune system and the global search capability of the problem has been well solved. An improved immune algorithm is essentially a parallel search algorithm, in which each experience to the entire population of impact, making the entire population toward the global optimum direction convergence, finally to obtain the global optimal solution.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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