Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

Path Planning for Mobile Robots in Irregular Environment Using Immune Evolutionary Algorithm

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Abstract: The traditional evolution algorithm usually traps into local optimization easily. Aiming to the drawback of evolution algorithm, we propose a novel mobile robot path planning approach of immune evolutionary algorithm in irregular environment. The advantages of this method lie in two aspects. The diversity of antibodies can be maintained. Meanwhile immunity operation and optimizing operator can be used to improve the global search ability. The results of simulation experiment show that immune evolution algorithm is feasible and efficient, because it enhances the performance and quality of mobile robot path planning.

1. INTRODUCTION

Path planning in an irregular environment is an important research area of mobile robots navigation technology, because a well path planning result can improve some properties of navigation and decrease some uncertain facts. The topic is also a flag of robot intellectualization. There are various traditional methods to resolve mobile robots path planning from now on, Grid Model (Payeur, P., 2004) and Artificial Potential Field(Zu, D., et al, 2004 and Cao Q. et al, 2006) are both classic approaches, Maybe they are good at the real-time but not good at the global path planning. With delving into those algorithms, some intelligent algorithms are imported into path planning research areas gradually. For instance: Neural network (Lebedev, D.V, et al, 2003 and Chan, H.T, et al, 1993), Genetic algorithm, ant colony (Hu Y., et al, 2004, M.Gemeinder, et al, 2003 and Zhong Y., et al, 2002) and so on. Genetic algorithm for path planning has strong abilities of parallel computing and global searching (Li Q., et al, 2000 and Hung, K., et al, 2007), however genetic algorithm has its own deficiency, it is short of institutive (Alvarez, A., et al, 2004) and GA apt to precocity, then lead into local minima (Yang Dadi, et al, 2006). At last the computation efficiency can not be assured.

Artificial immune system develops very fast recently which draws lessons from biology immune system principle and mechanism. Artificial immune system has powerful abilities of recognition learning and memory (Jiao LC, et al, 2000). Meanwhile, it also has self-organization property and diversity character. In this paper, we import immune principle and mechanism for reference, meanwhile evolution algorithm is combined with artificial immune to resolve mobile robot path planning problem. It's an innovation, because the algorithm can inhibit precocity phenomena in evolution algorithm and assure the planning accuracy. The properties of evolution algorithm are enhanced and the quality of path planning is improved.

2. PATH PLANNING ALGORITHM BASED ON IMMUNE EVOLUTION MECHANISM

2.1 Algorithm Steps

Based on immune evolution mechanism path planning algorithm, unknown best final results are considered as antigens in the path planning. Evolution processes are antibody matching with antigen processes. Immune evolution algorithms for mobile robot path planning steps are described as following:

STEP1: initialize the antibodies A of scale N.

STEP2: all the antibodies in the population are evaluated by fitness function.

STEP3: if the optimal individual in population satisfies with request condition, then output the result; otherwise, go to STEP4.

STEP4: use affinity degree mechanism to choose the best m antibodies, and then put them into the set of memory schema A_m. The others which have low fitness values put into another set A_r of scale r.

STEP5: each antibody of memory schema A_m must operate by immunity clone; T_i set is composed of each antibody clone operation result. The clone individual number of n keeps direct ratio with parents' fitness value.

STEP6: each new antibody of set T_i does hybrid mutation operation with mutation operator, and then we gain T_i'. The mutation extent is assured according to hybrid mutation probability function.

STEP7: after mutation, antibodies of set T_i' keep certain probability to vaccinate, and then we gain set *Ti''*.

STEP8: the antibodies of set *Ti''* must be re-evaluated by fitness function afresh, we choose appropriate antibodies from set *Ti''* according to annealing selection. Then the antibodies substitute or reserve parents' antibodies adding into set A_m.

STEP9: low fitness value antibodies or eliminated antibodies of antibodies of set A_r are supplied with new random production antibodies in order to keep diversity.

STEP10: Updates the antibodies total set $A = A_m + A_r$, then return to STEP3.

2.2 Path Encoding

A path can be seen as some polygonal lines which passes a series of coordinates nodes. A valid path corresponds with an antibody in the population, and a node coordinate can be seen as a gene fragment. Encode as following:

$$X = \{(x_1, y_1), (x_2, y_2)...(x_n, y_n)\} \quad (1)$$

Here (x_1, y_1) and (x_2, y_2) are the passing nodes coordinates successively.

2.3 Fitness Function

According to the request of mobile robot path planning, there are certain criteria to evaluate the quality of a path. For example: the total path length and smoothness, the robot obstacle avoidance times in real time due to path intersected with obstacle, and so on, those are some important facts. So the fitness function is decided by above three facts.

dist(X) represents the total length of path X in current environment. $d((x_i, y_i),(x_{i+1},y_{i+1}))$ is the distance from m_1 node to m_2 node. *corner(X)* denotes total rotation angle radian of path X in current environment, of which $angle(L_i, L_{i+1})$ is the angle between two polygonal lines. *avoid(X)* are intersection times of obstacle with path X in the current environment. C_1, C_2, C_3 are all constants, they represent the weight coefficients respectively and they're adjusted by the current environment and path planning request. n is the total number of the nodes. Fitness function *f(X)* and other relative formulas are given as following:

$$corner(X) = \sum_{i=1}^{n-1} | angle(L_i, L_{i+1}) - \pi | \quad (2)$$

$$dist(X) = \sum_{i=1}^{n-1} d((x_i, y_i), (x_{i+1}, y_{i+1})) \quad (3)$$

$$f(X) = C - C_1 dist(X) - C_2 corner(X) - C_3 avoid(X) \quad (4)$$

2.4 Hybrid Mutation

Among path planning processing, we modify turning point coordination to realize mutation operation. Here the numbers of modification turning points are defined as mutation extent.

On the one hand, mutation operation lets the algorithm has local random research ability. On the other hand, mutation operation should make the optimization antibodies jump out local convergence with a certain probability. It can be affirmed by simulation results of Part 3. Individual of set T_i operates with different extent mutation respectively in order to resolve the inherent contradiction of mutation operation. In the other word, hybrid extent mutation can be used to release the contradiction. An effective small extent mutation can optimize local area validly. A large extent mutation is used to improve global optimization ability.

Meanwhile, we choose appropriate probability function to control the ratio of antibodies in various extent mutations, $\{W_i\}$ is array of mutation extent and it's an increasing array. The antibodies mutation of probability P_i with W_i extent mutation:

$$P_i = \frac{W_i + C \times k \times f_p / W_i}{\sum_{j=0}^{n} (W_j + C \times k \times f_p / W_j)} \quad (5)$$

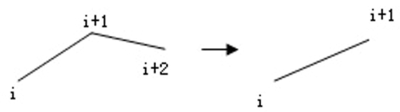
Here k is iterative calculation times in population. C is the constant. f_p represents weight of parents' antibodies affinity degree among the population and is defined as:

$$f_p = \frac{f_i}{\sum_{j=1}^{n} f_j}$$

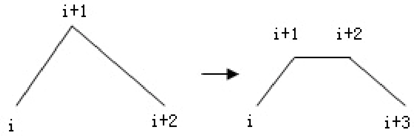
With iteration number increasing, the chief mutation transforms from large extent mutation to small extent mutation in time domain. In spatial domain, large extent mutation ratio of same parents' clone antibodies set in inverse proportion to same parents' affinity degree, which optimize time and spatial domain distribution of mutation extent and relieve contradiction between mutation operation local reaching and global reaching in certain extent.

2.5 Vaccinations

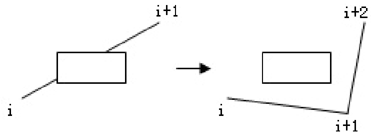
Using its own information to resolve problem is the character of immune evolution algorithm that is better than genetic algorithm. Vaccinations are to extract priori information. The vaccinations of path planning are the processing of local optimization association with global solution scheme. Using current environment character and some local known rules (as Fig.1 shown) help antibodies do vaccination operation that can improve antibodies affiliate degree and quicken convergence speed.



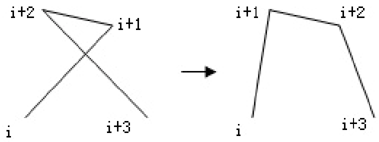
(*a*) Delete Operation



(*b*) Smoothing Operation



(*c*) Avoiding Operation



(*d*) Interceptive Operation

Fig.1 Crossover Operation

2.6 Annealing Selection

To prevent antibodies population mature much earlier and keep their diversity, firstly, antibodies after mutation are re-evaluated through fitness function. Secondly, choose appropriate antibodies into the next generation antibodies population instead of parents' antibodies by annealing selection principle. In other words, chosen antibodies X substitute of parents' antibodies into next generation in set Ti'' of n scale with probability $P(X)$:

$$P(X) = \frac{e^{f(X)/t_k}}{\sum_{i=1}^{n} e^{f(Xi)/t_k}} \tag{6}$$

Here t_k is temperature control sequence of trend to 0 with increasing iterative computing times of population.

3. COMPUTER SIMULATIONS

The simulation experiment is adopted Visual C++ to realize the environment platform, and effectiveness of above-mentioned algorithm is verified by the simulation experiment. On the simulation platform, a path panning result have been shown from start point of top left corner to goal point of right lower, the irregular obstacle environment is illustrated as shown in Fig.2.

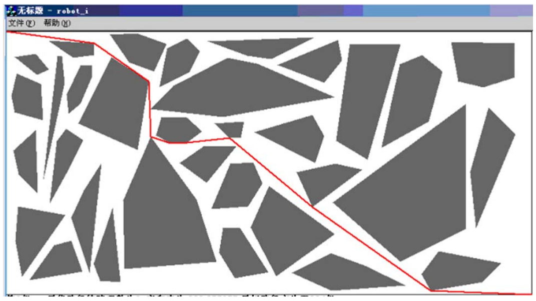


Fig2. Iterative process of immune evolutionary

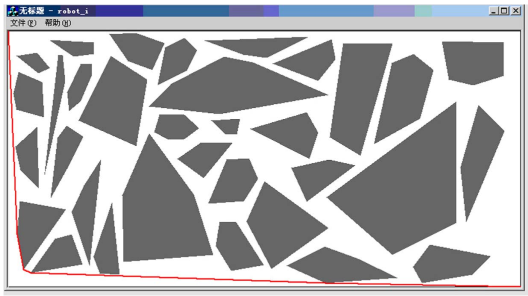


Fig3. Local optimal solution

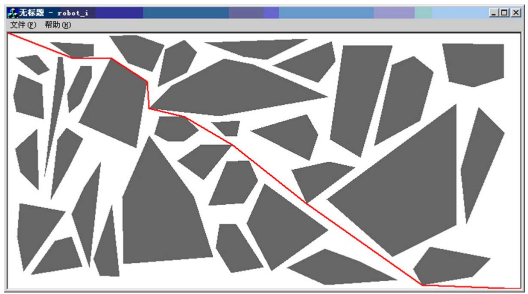


Fig.4 The best result of immune evolution

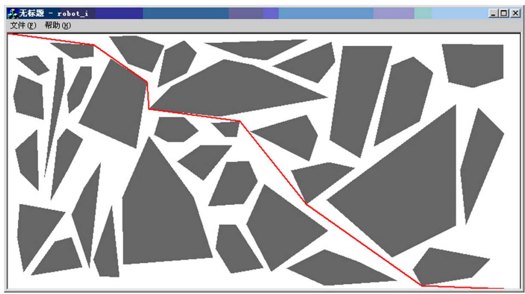


Fig.5 The best result of genetic algorithm

We give the following experiment data: population size is 50, proportion of memory set is 0.3, and elimination ratio is 0.2, At last we achieve 50 times simulation results with Immune Evolutionary Algorithm and Genetic Algorithm respectively, then the experimental results are recorded.

Figure 2 is the intermediate solution of the immune evolutionary iterative process. The local optimal solution as is shown in Figure 3. The best result of those 50 times simulation results is drawn in Figure 4 by the immune evolutionary algorithm for path planning. Figure 5 is shown the best result of genetic algorithm of those 50 times simulation results. Besides, table 1 is part of sampling simulation experimental result, and table 2 is the statistic experiment result. In this paper, the optimized immune evolution algorithm for path planning can not enter into premature easily. Additional, the quality of solution enhance greatly and we gain better result.

Table 1 Part of experimental data

	Immune Evolutionary		Genetic Evolutionary	
Index	Convergence Gap	Adaptation Degree	Convergence Gap	Adaptation Degree
1	173	356.1	190	235.2
2	229	325.5	103	317.2
3	131	355.4	259	242.6

Table 2 Comparison of each path planning result

	Immune Evolution	Genetic Algorithm
Solution of Average Fitness	334.1	252.2
Successful Convergence Ratio	96%	72%
Optimal Solution Fitness	356.4	337.3
The Worst Solution Fitness	142.9	141.0
Average Convergence Gap	214.7	208.5

4. CONCLUSIONS

In this paper, we use the immune evolutionary algorithm to solve mobile robot path planning problem in irregular environment, it provides a good proposal of combined immune mechanism with evolutionary algorithm for path planning, and the approach is feasible and efficient. We exploit the methods of probability function hybrid extent mutation. Meanwhile, simulated annealing algorithm prevents local optimization and quickens the speed of convergence. Both of them improve the quality and efficiency of path planning to a certain extent.

5. ACKNOWLEDGEMENTS

This work was supported by Basic Research Project of China under Grant No.A1420060159.

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