Mobile Robot Static Path Planning Based on Genetic Simulated Annealing Algorithm

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Abstract: Robot path planning in a static environment is studied and Genetic Simulated Annealing is proposed. In the genetic algorithm, large-scale initialization combined with the selecting mechanism is applied to initialize the starting point out of the barrier area. A simple real one-dimensional coding technique is used; The feasibility, smoothness and length of a path determine an efficient adaptive function,and an effective genetic operators is set up . In the simulated annealing, random moving rule uses Metropolis rule and devise efficient temperature update function.The simulation result confirms that the genetic simulated annealing algorithm is feasible and efficient for mobile robot path-planning.

Key words: path-planning; mobile robot; Genetic algorithm; simulated annealing algorithm

1 Introduction

In recent years, robot path planning has been a research study in one of the hot. The objectives of the study is how to find a reasonable and efficient robot path which can search from the starting point for the robot to the target point and be able to avoid obstacles.Many scholars at home and abroad have studied mobile robot path planning problem in depth research, and a variety of path planning methods have been put forward, such as: may view law[1][2], graph search method, the artificial potential field method[3] and so on. However, these methods search a larger space,and exist the combinatorial explosion problem, and it is difficult to meet the requirements of real-time search, the failure of the planning.

Genetic algorithm with robust, flexible, in the search for species not easily fall into local minimum points, etc. [4], but in the practical application of the process, it may also have a precocious phenomenon, the capacity of poor local optimization problem. And simulated annealing has a strong local search ability, so an effective way to solve the above problems is to combine genetic algorithm and simulated annealing,

2. Problem Description

The effective description of activity space for the robot is known as the environment model. The assumption that the environmental data of the overall situation are predictable, and therefore environment modeling that is using a mathematical method to describe the robot's outside world. There are a lot of modeling methods, such as space law, the lattice method, unit tree method, the polygon method, such as generalized cone method. In which, polygon method is one of the polygon approximation with obstacles, is a high-level description of the environment depends on the topology. Polygon selection method is used in this paper. Robot in the two-dimensional work environment, with two-dimensional environment in which to express the coordinates of the robot working environment. As shown in Figure 1: Polygons denoted as barrier, and in the procedures, polygon vertex coordinates express obstacles. Reduce the robot as a particle, said that obstacles polygon robot in accordance with the scope to reduce the expansion of a certain proportion.
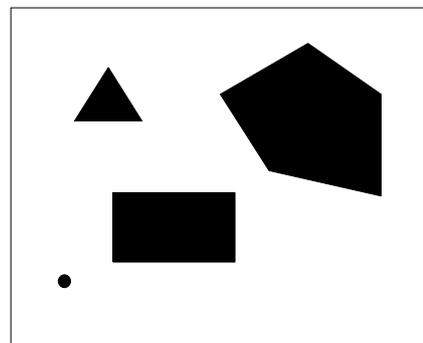
Figure 1. The establishment of the robot environment
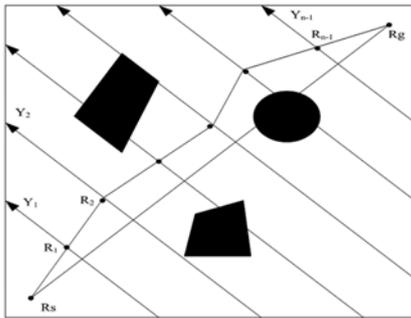
Figure 2. encoding technology

3. The parameter setting of Genetic simulated annealing algorithm

The simulated annealing algorithm combined with the genetic algorithm offers a strong global and local search capabilities .

3.1 Path coding method

Using the technology to simplify the length coding, that is, the point on the path of two-dimensional coding simplified to one-dimensional coding. Since each point on a path in the vertical Yi on, so as long as the path to point to know the abscissa x, longitudinal coordinate y can be calculated in accordance with the equation of vertical line. Therefore, we only put in the calculation of the abscissa as a gene encoding, encoding technology as shown in Figure 2, it saves computing time. Coordinates use of real-coded approach, because in the two-dimensional work environment, the location of robot and obstacles can be the location coordinates directly with real numbers that if we want to make these floating-point numbers into binary, it would be a waste of time, would increase in computation, so the form of floating-point numbers was used.

3.2 Choice of fitness function

Fitness function is important factor affected genetic algorithm convergence and stability, but also the key aspect converted a given goal to a system control goal.

Taking into account the smoothness and the lengthof the path, the fitness function *fit1* is denoted: $fit1 = \sum_{i=1}^{n-1} e^{\alpha \frac{l_i}{L_i}}$ .Taking into account the feasibility of the

path, that is, between the barrier and want to maintain a certain distance, fitness function *fit2* is denoted: $fit2 = \sum_{i=1}^{n-1} e^{\beta(d-g_i)}$. The final fitness function is defined as:

$$f = fit1 + fit2 \qquad (1)$$

Where, L_i is the distance linked the Connecting node to the target node R_g . l_i is the distance linked the Half-way point on the path to the target node R_g. g_i is the minimum distance linked the Half-way point on the path to the the obstacles vertex. d is the robot safe distance, α, β are the parameters. These distance parameters in the environment specific shown in Figure 3
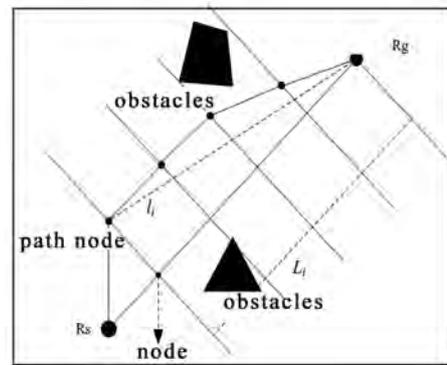
Figure 3. Fitness function of the parameter values
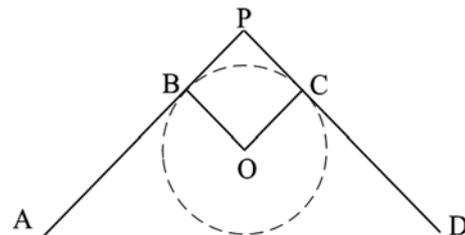
Figure 4 Smoothing the path diagram

3.3 Genetic operators of selection

2.3.1 Operator selection

In this article, operator selection used the proportional selection operator, also known as rotating disk gambling law.It is a playback method of random sampling. The basic idea is: the probability of each individual being selected is inversely proportional to the size of their fitness. For each individual use of the fitness function to achieve their fitness value, then use of the probability

function to select Whether or not this individual into the next generation. Probability function as follows:

$$p_{is} = \sum_{j=1}^{M} f_j / f_i \quad (i=1, 2, ...,M) \qquad (2)$$

Where, f_i is the ith individuals's fitness function value, M is the number of individual species. The smaller the fitness function value is, the greater the likelihood of survival is, that is, there is the higher opportunity to be selected; the other hand, The greater the fitness function value is, the smaller the likelihood of survival is.

2.3.2 Crossover operator

Crossover operator applied non-symmetric single-point crossover strategy. A pair of individuals Of the parent, that is, two paths, and then on each path , randomly selected a cross-point ,two cross-point on the two paths do not have to be in the same location, then exchanged the two cross - point in the crossover probability Pc, and received the two new path after the cross. This is the so-called non-symmetric single-point crossover strategy.

2.3.3 Mutation operator

Mutation operation is randomly changed coordinates on a half-way point of the path. First of all, the use of heuristic variation, so that all the path are optimized into feasible paths, and then choose a variation point randomly, and finally mutated the variation point in the probability Pm. Heuristic variation method include the followings: a. moving a point: In a path, if the middle segment $\overline{R_i R_{i+1}}$ through the barrier, then the node Ri $(i = 1,2, ..., n-1)$ is moved. Such as ,for the first segment $\overline{RsR_1}$, if through the obstacles, then the node R_1 is moved. b. deleting a point: In a path, if the half-way node R_{i-1} and R_{i+1} are connected, and the connecting line does not cross the barrier, then delete the middle node Ri $(i = 1,2, ..., n-1)$.

3.4 Randomly mobile guidelines

The reason why simulated annealing is able to jump out of local optimal solution, that it can accepts not only the optimized solutions but also the deteriorated solutions in a limit scope, which is the essential difference between the simulated annealing algorithm

and the local search algorithm. Then the necessary to use an acceptable optimal solution criteria to determine whether they were accepted. In this paper, if the *ith* individual evoluted to generate i 'th new entity, then whether or not to accept the i'? we can see from the discussion of 2.2, the most commonly criterion is the Metropolis criteria, then according to formula (1) to determine the probability of:

$$p(i \Rightarrow i') = \begin{cases} 1 & f(i') \le f(i) \\ \exp\left(\dfrac{f(i) - f(i')}{t}\right) & f(i') > f(i) \end{cases} \qquad (3)$$

Where t is the control parameter, $f(i)$, $f(i')$ is the objective function values (fitness function value)of the individuals i and individual i'.

3.5 Temperature update function

The performance of simulated annealing algorithm depends mainly on the annealing function which controlled the declined process of the temperature. In this paper, the annealing function from the literature: $T_k=T_0/k^m (k=1, 2, 3...)$, that is

$$T_k = \begin{cases} T_0 & k = 1 \\ \left(\dfrac{k-1}{k}\right)^m T_{k-1} & k \ge 2 \end{cases} \qquad (4)$$

Where: $T_0 > 0$ is the initial temperature, $m \ge 1$ is a given constant. It is cleard that: the annealing function defined by (4) is inversely proportional to iteration number (ie, annealing time) ' m-th: the smaller m is, the more slowly temperature dropped. In this way, through the appropriate choice of the value of m can control the rate of the temperature decline. In this experiment, $m = 5$. At the same time, we can see: When k was small, T fell fast; and k is large, Tfell slow. This is more in line with the original intent of the physical annealing process.

3.6 Smoothing the path

The planning path from above algorithm was a path-point sequence constitutes of some points, The path of the connection point was broken line, and it must be smooth to enhance the stability of the robot running. Consider the path which use interpolation smooth may

deviate from the original sequence and through the obstacles,in this paper ,arc line around the corner replace the broken line with a simple method. Figure 5 shows a specific process, the node P in the BC division with arc transition, in order to facilitate the determination of the transition arc, it is desirable that the arc of the node from the same cut points, such as from 0.2 meters. The distance determined, the radius of the arc and the center also received. Finally, the path is smoothed to be ABCD, is composed of a straight line and arc, which is simple, and there will be no question of crossing the barrier.

3 the method of path planning based on genetic simulated annealing in static environment

The steps of the robot global path planning based on genetic simulated annealing in static environment as follows:

1. Set up size M of groups. Initialize counter genetic algebra: $gen = 0$; Set up the initial temperature parameter $T = T_0$; randomly generate initial path set $P (gen)$.

2. Evaluate fitness in each of the path of $P (gen)$: f_{p1}, $f_{p2} ..., f_{pm}$.

3. Following the implementation of the existing stocks until the next generation to produce a new population:

(1)defined by 2.3.1 of the selection operator in the path from parent to offspring copy the path below: $P_s (gen)$ selection [P (gen)].

(2) defined by 2.3.2 of the crossover operator for offspring crossover path: from

$P_s (gen)$ in the first i individuals $P_{si} (gen)$ and j individuals $P_{sj} (gen)$ new individual cross-$P_{ci} (gen)$ and $P_{cj} (gen)$, and calculate the $P_{ci} (gen)$ and $P_{cj} (gen)$ of the value of fitness function.

(3) According to the formula 5,6 to determine to accept $P_{ci} (gen)$, $P_{cj} (gen)$ or reject $P_{ci} (gen)$, $P_{cj} (gen)$, then the new group $P_c (gen)$ is obtained after the cross-annealing.

$$p_i = \begin{cases} 1 & f(CI) \le f(SI) \\ \exp\left(\dfrac{f(SI)-f(CI)}{T}\right) & f(CI) > f(SI) \end{cases} \quad （5）$$

$$p_j = \begin{cases} 1 & f(CJ) \le f(SJ) \\ \exp\left(\dfrac{f(SJ)-f(CJ)}{T}\right) & f(CJ) > f(SJ) \end{cases} \quad （6）$$

(4) Mutation operator defined by the 2.3.3 operate the offspring path mutation , Individuals of the first i get a new individual variation $P_{mi} (gen)$,then the formula (3) indicated the probability of acceptance of $P_{mi} (gen)$ individual. then the new group $P_m (gen)$ is obtained after the final annealing variant.

(5) end of inner loop to determine whether the conditions to meet, if not met, then: $P (gen +1) = P_m (gen)$, $gen = gen +1$, go to step (1); if the meet is turning to step 4.

4. Determine the termination condition. Does not meet the termination conditions are: $P (gen) = P_m (gen)$, $gen = 0$; by cooling the temperature parameter update table T, turn to Step 3; if the termination of the conditions to meet, then turn to Step 5.

5. According to the method given in 2.6 to enable a smooth optimal path.

4 Simulation results

The followings are the two simulation results used genetic simulated annealing algorithm for robot path planning. The simulations were realized in Visual C + +6.0, two simulation results in Figure 6 and Figure 7. The planning environment as shown In Figure 6 and Figure 7, the robot reduced to a particle, that the static polygon obstacles and obstructions in accordance with the ratio of robots to carry out a certain narrowing of the outer expansion, R_s denote as the starting point, R_g denote as the target point.

The two environments as shown in Figure 6,7 used in exactly the same genetic algorithm parameters are: population size $M = 30$, crossover probability $P_c = 0.8$, mutation probability $P_m = 0.01$, the length of individual coding $n = 16$, that is, a path by 16 points. Both cases on behalf of, respectively, 40 iterations, 45 generation, the optimal path in the curve shown in Figure5,6, and the path generated is not the peak point. Map, respectively, showing their best to walk a specific path.
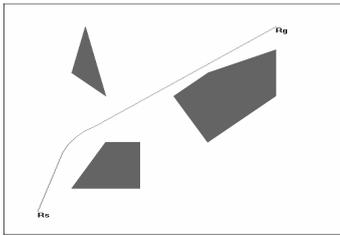
Figure 5. Simulation result 1
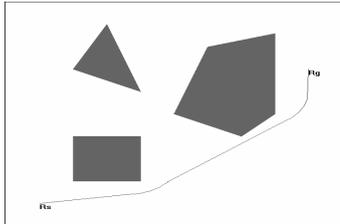
Figure 6. Simulation result 2

5 Conclusion

Mobile Robot Static Path Planning Based on Genetic Simulated Annealing Algorithm was studied, and the path planning algorithm is realized. This method overcomes the shortage individual used genetic algorithm path planning, effectively improve the computing speed of the path planning and ensure the quality of path planning. Optimal path in the output after the performance, taking into account the impact of robots,

improve the smoothness of the robot path. The simulation results show that the method to achieve an effective static global path planning tasks, and make up for local convergence, the issue of combinatorial explosion, such as inadequate.

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