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Lunar Rover Path Planning Based on Comprehensive Genetic Algorithm Based on Slip Prediction

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Lunar Rover Path Planning Based on Comprehensive Genetic Algorithm Based on Slip Prediction

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Abstract. Aiming at the problem that the lunar rover path planning algorithm generally has slow convergence rate, falls into local optimal solution, neglects the mutual applicability of environment modeling technology and path planning algorithm, a comprehensive genetic algorithm based on virtual three-dimensional model is proposed. By setting the genetic factor unchanged, the terrain comprehensive cost function is added to set the fitness function. Using genetic algorithm and improved comprehensive genetic algorithm, after 100 simulation experiments, the improved comprehensive genetic algorithm has good search performance, fast convergence and high stability. The key words of this paper are as follows: path planning, terrain comprehensive cost function, genetic algorithm.

1. Introduction

The lunar rover is an effective tool for moonwatch detection. During its inspection, an important task is to carry out path planning. Path planning is divided into map-based global path planning and sensor-based partial path planning. The so-called global path planning is to find the global optimal path according to one or several optimization criteria (such as the shortest path, the least time, etc.) when the environment is completely known. Path planning research began in the 1970s[1], and from that time back to the present, path planning algorithms of various forms have been proposed and are recognized. Contains both traditional A* algorithms[2], Genetic algorithm[3], Also comes with some new intelligent algorithms, such as Ant Colony Algorithm[4], Neural network algorithm[5], Particle swarm optimization[6], As far as the genetic algorithm is concerned, the search efficiency is low, the obstacle avoidance effect is not good, and the algorithm complexity is too large, resulting in an inability to obtain an excellent solution.

In this paper, the existing genetic algorithm is easy to fall into the local optimal solution, comprehensively consider the lunar terrain environment information, and integrate the pass-through cost function by adding the slip factor prediction of the terrain factor[7]. Using MATLAB simulation experiment, keeping the terrain parameters unchanged, adjusting the slip passability function parameters, comparing 100 experimental simulation results, the integrated genetic algorithm evolutionary algebra is less than the traditional genetic algorithm. The improved genetic algorithm improves the smoothness of the lunar rover path planning, shortens the length of the path, and saves the time and evolution of the path planning.

2. Integrated genetic algorithm

2.1. Establishment of genetic algorithm path planning model

In this paper, the genetic coding uses real number coding. For each chromosome in the genetic algorithm, there is one solution. In the path planning process, the gene consists of several intermediate points through the starting point, the end point and the path planning[8]. The start point (X_1, Y_1, Z_1), the end point (X_n, Y_n, Z_n), and the $n-2$ intermediate point shown in figure 1 constitute one chromosome carrying path planning information from the start point to the target point.

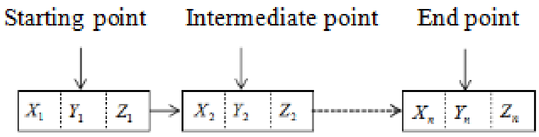

Figure 1. One chromosome with n genes in path planning.

Therefore, a complete robot path is an ordered combination of several line segments, using the (P) express, as in formula (1):

$$P = \sum P_i \tag{1}$$

P_i Representing the i vector representation of a segment of a straight line.

2.2. Initial population generation

In the process of generating chromosomes, starting from the starting point, randomly select the transitive nodes of the neighbor nodes of the current node, add their coordinates to the chromosome, and so on, until a target point is found, and one chromosome is generated[9]. Repeat the above operation to reach the initial target population and terminate the loop.

2.3. Genetic manipulation (selection, crossover, mutation operator design)

The genetic algorithm was proposed by Professor J. Holland of the University of Michigan in the United States. It is an adaptive algorithm for bionic global optimization probability search[10]. The preset parameters required by the algorithm include initial population number, maximum evolution algebra, crossover probability and mutation probability.generally include three processes of selection, intersection and mutation[11]. In the process of algorithm evolution, the crossover and mutation probability affect the local part of the algorithm. Global search capabilities, fixed crossover probabilities, and mutation probabilities do not guarantee that the algorithm converges faster and searches for global optimal solutions[12]. Through continuous iteration, the optimal solution of the problem is finally obtained.

- This algorithm adopts elitist selection strategy, that is, replacing some poor individuals with some excellent individuals[13].
- Cross-operation is a process simulation of genetic recombination in nature, and is the main method for genetic algorithms to generate new individuals[14].In this paper, some of the paper uses partial mapping to perform chromosome crossover operations to generate two random numbers m, n, the exchange of gene fragments between m and n on the X, Y chromosome.Cross probability formulas such as (2):

$$P_c = P_{cmax} - \frac{(P_{cmax} - P_{cmin})(F_c - F_{min})}{F_{max} - F_{min}} \tag{2}$$

In the form: P_c Indicates the crossover probability in dynamic path planning; $P_{c\max}$ Indicates the maximum value of the crossover probability; $P_{c\min}$ Indicates the minimum value of the crossover probability; $F_{\max}$ Indicates the maximum fitness value in the population; $F_{\min}$ Indicates the minimum fitness value; F_c Indicates the larger fitness value of the two individuals to cross.

- The mutation operation simulates the process of mutation in the natural world[15]. During the iterative process, the genes on the chromosome are randomly mutated to produce new individuals. Variation probability formula such as (3):

$$P_m = P_{m\max} - \frac{(P_{m\max} - P_{m\min})(F_m - F_{\min})}{F_{\max} - F_{\min}} \tag{3}$$

In the form: P_m Indicates the probability of mutation in dynamic path planning; $P_{m\max}$ Indicates the maximum value of the mutation rate; $P_{m\min}$ Minimum value indicating the probability of mutation; $F_{\max}$ Indicates the maximum fitness value in the population; $F_{\min}$ Minimum fitness value; F_m Indicates the fitness value of the individual to be mutated.

3. Design of fitness function for slip prediction

In the genetic algorithm, the fitness function is a criterion for judging the individual's ability to survive in the population, which is determined according to the objective function. In solving the optimal path, the larger the value of the fitness function, the better. In the path planning of this paper, the shortest path and the smallest evolutionary algebra are the primary fitness functions. In addition, this article adds a terrain passivity cost function. The topographical passivity function is a function to evaluate the ability of topographical passivity. This function takes into account factors such as terrain slope, terrain roughness, and obstacles. In this paper, the slip factor is added to the consideration factor to form a terrain passivity cost function based on slip prediction. Using this function, you can evaluate the passability of the path between two points. Here, the above terrain comprehensive cost function $f(p,n)$ is incorporated into the fitness function of the genetic algorithm, and the integrated genetic algorithm is used for path planning.

The terrain comprehensive cost function for setting the node p -to-node n gene fragment is as follows:

$$f(p,n) = f_1 \times f_{trav}(p,n) + f_2 \times f_{risky}(p,n) + f_3 \times f_{guide}(p,n) + f_4 \times f_{smooth}(p,n) \tag{4}$$

In the form: $f_{trav}(p,n)$ is the passability cost function from node p to node n (generally 0 or 1); $f_{risky}(p,n)$ is the potential risk cost function; $f_{guide}(p,n)$ is the cost function of path directivity, which is related to the slope angle of the terrain; $f_{smooth}(p,n)$ is the path smoothness cost function takes a fixed constant value; f_1, f_2, f_3, f_4 is the weight of $f_{trav}(p,n)$, $f_{risky}(p,n)$, $f_{guide}(p,n)$, and $f_{smooth}(p,n)$ respectively,they are generally treated as the same fixed constant value. Then, the extendable slip-through passability cost function $f(p,n)$ is added to the fitness function of the genetic algorithm to form a new fitness function $f'(p,n)$. The formula called the comprehensive fitness function $f'(p,n)$.The formula is as follows:

$$f'(p,n) = f(p,n) + f_0(p,n) \tag{5}$$

$f'(p,n)$ is the fitness function of the function of the integrated genetic algorithm; $f(p,n)$ is the terrain comprehensive cost function; $f_0(p,n)$ is the fitness function based on the genetic algorithm.

4. Simulation experiment analysis

This paper uses a PC, based on the Matlab 2014 environment to create a virtual three-dimensional terrain environment $(21 \times 21 \times 21)$, virtual three-dimensional space abstraction into the grid, set the starting point and end point and height value of the search path. Set the initial population to 30, and the maximum evolutionary algebra to 200 generations. As can be seen from Figure 2, the three-dimensional genetic algorithm path planning is more intuitive and effective than the two-dimensional grid model.

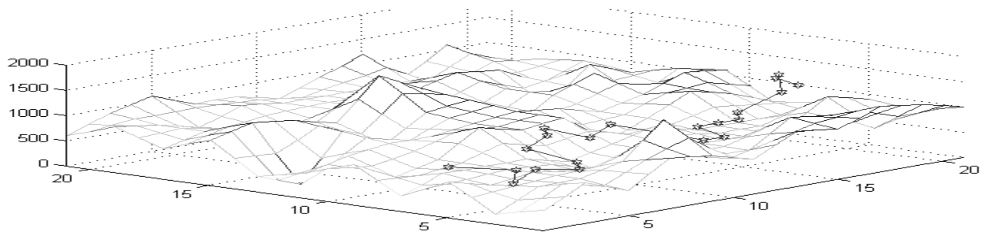

Figure 2. Based on genetic algorithm.

In this paper, genetic algorithm and integrated genetic algorithm (IGA), one evolutionary algebra and comprehensive fitness change diagram, as shown in Figure 3 and Figure 4. It can be seen from Figure 3 that the basic genetic algorithm has evolved into the local optimal solution after about 10 generations, the optimal solution is updated after the 50th generation, and the optimal solution is obtained once in the 140th generation. The comprehensive fitness value is 130. It can be seen from the path plan of the integrated genetic algorithm in Figure 4 that the optimal solution is obtained once in 20 evolutionary algebras, and the comprehensive fitness value is 125. The path planning time is shortened to some extent, and the work efficiency is improved.

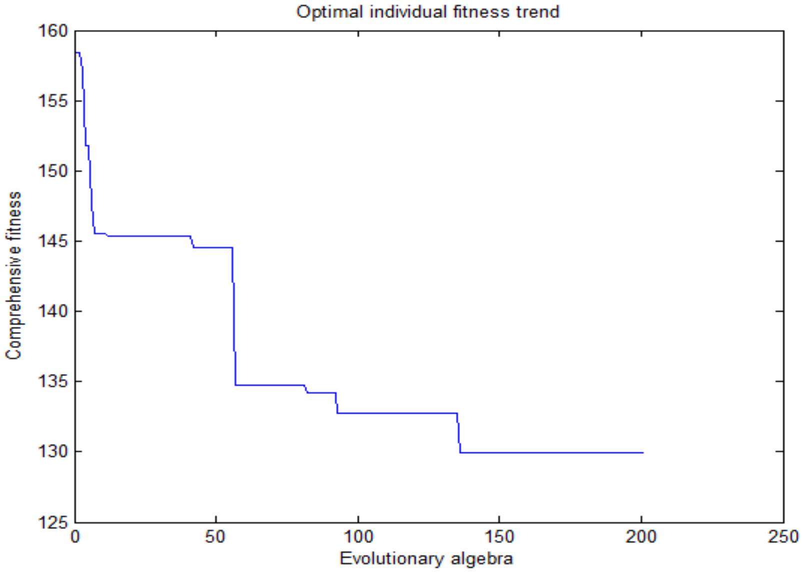

Figure 3. Genetic algorithm.

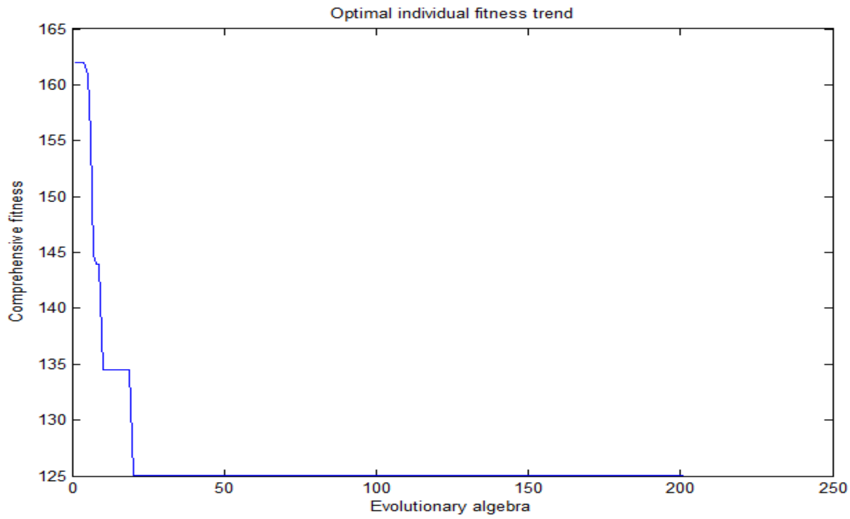

Figure 4. Integrated genetic algorithm.

In order to further prove the rationality of the algorithm and avoid the influence of accidental factors on the algorithm, the two path planning algorithms are tested 100 times respectively. The statistical experimental results are shown in Table 1. It can be seen from Table 1 that the average maximum path of the integrated genetic algorithm is 34.7% shorter than the maximum path of the genetic algorithm, the average fitness value is increased by 12.4%, and the average evolutionary algebra is reduced by 49.2%.

Table 1.performance comparison between genetic algorithm and improved genetic algorithm.

Algorithm name	Average maximum path(/km)	Average comprehensive fitness	Average evolutionary algebra(/times)
Genetic algorithm	49.6	120.40	128
Integrated genetic algorithm	32.4	135.38	65

5. Conclusion

In order to solve the problem of slow convergence and easy to fall into the local optimal solution in the path planning problem of genetic algorithm, the terrain synthesis cost function is introduced to design the fitness function. The crossover operator and mutation operator are obtained dynamically according to the comprehensive fitness, and a path planning algorithm based on comprehensive genetic algorithm is proposed. Through the experimental simulation in the three-dimensional simulation environment, the analysis of the results, the improved synthetic genetic algorithm in search of the path, the time efficiency compared with the basic genetic algorithm has been improved. The results show that the improved algorithm can achieve a good path planning effect under certain conditions. In reality, the terrain is very complex, Path planning based on one algorithm alone can not achieve ideal results. 3D environment reconstruction is the focus of path planning, so constructing complex dynamic path planning is the next research focus.

Acknowledgments

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References

[1] Anish Pandey, Dayal R. Parhi. Optimum path planning of mobile robot in unknown static and dynamic environments using Fuzzy-Wind Driven Optimization algorithm[J]. Defence Technology,2017.

[2] Ren Yujie, Fu Lixia, Zhang Yong, Mao Jianlin. Dynamic Path Planning of Robot Based on Smooth A* Artificial Potential Field Method[J].Software Guide, 2018,17(01):8-10.

[3] N. Weerayuth , N. Chaiyaratana.Closed-loop time-optimal path planning using a multi-objective diversity control oriented genetic algorithm[P]. Systems, Man and Cybernetics, 2002 IEEE International Conference on,2002.

[4] Cai Wen,Yansong Deng. Global path planning of Multi-robot Fish based on adaptive ant colony algorithm in dynamic environment[P]. 4th International Conference on Renewable Energy and Environmental Technology (ICREET 2016),2017.

[5] Gong Mengmeng. Research on path planning method of mobile robot based on neural network [D]. Harbin Institute of Technology, 2017.

[6] Lu Dan. Application of particle swarm optimization in path planning of mobile robots [D]. Wuhan University of Science and Technology, 2009.

[7] Ha, C., Yoon, J., Kim, C., Lee, Y., Kwon, S., & Lee, D. (2018). Teleoperation of a platoon of distributed wheeled mobile robots with predictive display. Autonomous Robots, 42(8), 1819-1836.

[8] Ha C, Yoon J, Kim C, et al. Teleoperation of a platoon of distributed wheeled mobile robots with predictive display[J]. Autonomous Robots, 2018, 42(8):1819-1836.

[9] Ha, Changsu, et al. "Teleoperation of a platoon of distributed wheeled mobile robots with predictive display." Autonomous Robots42.8(2018):1819-1836.

[10] WANG X P, CAO L M.Genetic Algorithm Theory, Application and Software Implementation[M].Xi’an: Xi’an Jiaotong University Press, 2002:2-5.

[11] Wu, Meihua, et al. "Path planning of mobile robot based on improved genetic algorithm." Chinese Automation Congress 2018.
[12] Huang Chao. Research on path planning of AGV system based on wireless network [D]. Shanghai: East China University of Science and Technology, 2015.
[13] Hong Qu,Ke Xing,Takacs Alexander.An improved genetic algorithm with co-evolutionary strategy for global path planning of multiple mobile robots[J].Neurocomputing,2013(120):509-517.
[14] Yuan Guangming, Yan Yunfei, Ding Chengjun, Zhang Peng. AGV Path Planning Based on Improved Genetic Algorithm[J].Journal of Beijing Union University,2018,32(01):65-69.
[15] Wu M, Chen E, Shi Q, et al. Path planning of mobile robot based on improved genetic algorithm[C]// Chinese Automation Congress. 2018.