IOP Conf. Series: Materials Science and Engineering **758** (2020) 012026 doi:10.1088/1757-899X/758/1/012026

A Mobile Robot Path Planning Scheme for Dynamic Environments

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Abstract. This paper proposes a four-direction search method for obstacle avoidance of mobile robots, and the collision energy of obstacles is modeled based on the neural network. For comparison and discussion purposes, the different invariant step lengths are tested in the static environment. To take the advantages of the large and small step lengths effectively, a variable step length method is adopted to improve the performance, such as less iteration number and lower total energy. The variable step length method is also applied to the dynamic environment to explore the real-time performance for path planning. Simulation results demonstrate the effectiveness and practicability of the presented scheme.

1. Introduction

In the field of robotics, one of the hot research issues is how to make a mobile robot move to the goal point as quickly as possible with obstacle-avoidance in an environment [1-10]. Generally speaking, the obstacle-avoidance problem solving of a mobile robot can be transformed into path planning. The set of a series of points or lines interconnecting from the initial point to the goal point is called a path, and the decision to form the path is called path planning. Main problem to be solved in the process of path planning can be described as generating a path from the initial point to the goal point, using algorithms to make a mobile robot avoid obstacles in the path, and making the generated path as smooth as possible [1]. The path planning problem of a mobile robot can be divided into global path planning and local path planning, which depends on the environment of the mobile robot. In global path planning, the environment around the mobile robot is known, and environmental information is static and known. In local path planning, the environment surrounding the mobile robot is unknown or partially known, and then, environmental information can be seem dynamic [2].

In the field of path planning, many scholars have conducted a series of studies. For path planning in a static environment, Priyanka Sudhakara applied an enhanced artificial potential field method to improve the oscillations in navigable trajectories. However, the final generated path was not smooth enough [3]. For the dynamic environment situation, Huckleberry Febbo put forward a method, in which a hard constraint formulation was proposed to solve the moving obstacle avoidance problem of large, high-speed autonomous ground vehicles in an unstructured environment. Nevertheless, after the sensors detected obstacles, it cannot build a suitable mathematical model in the map [4]. Mohamed Elhoseny presented a modified genetic algorithm based on Bezier Curve for path planning in a dynamic environment, in which the local optima may be considered further [5]. In this paper, we propose a mobile robot path planning scheme for a dynamic environment, which can obtain a smooth optimal path and avoid local optima.

2. Problem Formulation

In this section, the algorithm for path planning based on neural network is described for discussion.

2.1. Formulation of Collision Energy Function

Normally, if we have information about the location and shape of the obstacle, we can reformulate the obstacle as a stationary convex polygon or a circle for a known two-dimensional environment [6-8]. For the path planning problem, the collision energy $G(i)(x_i, y_i)$ of every coordinate point is obtained by using neural network [6-8]. In the neural network structure, the input layer is set as the environmental coordinate point. The first hidden layer $\boldsymbol{U}$ is determined by the shape of the environmental obstacles. Based on the neural network, every convex polygon can be represented as a number of closed line segments [6-8], and the line can be described as·

$$w_x x + w_y y + \sigma = 0 \tag{1}$$

where w_x, w_y and σ are the line function coefficients. We reformulated the j-th obstacle as a rectangle and we have the information of its four sides as follows:

$$\begin{cases} w_{xj1}x_i + w_{yj1}y_i + \sigma_{uj1} \geq 0 \\ w_{xj2}x_i + w_{yj2}y_i + \sigma_{uj2} \geq 0 \\ w_{xj3}x_i + w_{yj3}y_i + \sigma_{uj3} \geq 0 \\ w_{xj4}x_i + w_{yj4}y_i + \sigma_{uj4} \geq 0 \end{cases}$$

where σ_{ujk} is its threshold coefficient, and w_{xjk}, w_{yjk} are weight values of the input neurons x_i, y_i to the jk-th hidden layer neuron with $k = 1,2,3,4$. For the k-th side of j-th obstacle, the first hidden layer neuron function is set as

$$u_{jk}(x_i, y_i) = \frac{1}{1 + e^{-(w_{xjk}x_i + w_{yjk}y_i + \sigma_{ujk})/T}} \tag{2}$$

where T is the positive design parameter. In addition, If the j-th obstacle is circular, r is its radius, and C_{jx} and C_{jy} are the center coordinates, then we can set its first hidden layer neuron function as

$$u_j(x_i, y_i) = r - (x_i - C_{jx})^2 - (y_i - C_{jy})^2 \tag{3}$$

The second hidden layer neuron function for the j-th obstacle consisted of k sides is taken as

$$o_j(u_{j1}, u_{j2}, .., u_{jk}) = \frac{1}{1 + e^{-(\sum_{i=1}^{k} u_{ji} - \sigma_{oj})/T}} \tag{4}$$

where $\sigma_{oj} = k - 0.5$ (for the circular obstacle, $\sigma_{oj} = 0.5$). For an environment with n obstacles, we can obtain the energy of a point as

$$g_i(o_1, o_2, ..., o_n) = \sum_{j=1}^{n} o_j \tag{5}$$

It is worth mentioned that the distributed shape of collision energy by Eqs. (2) and (4) is influenced by the design parameter *T*. When parameter *T* is larger, the shape is more smooth.

In view of the above-mentioned discussion, we can obtain the energy distribution associated with obstacles in the environment.

2.2. Four-direction search scheme

In this section, we propose a four-direction search method for mobile robot path planning. we connect the start point to the goal point as the initial path, and then divide the initial path into many equally-long line-segments as shown in Figure 1(a). Different from the search algorithm of Refs. [6,7], we present a four-direction search method for mobile robot avoidance obstacle, shown in Figure 1(b).

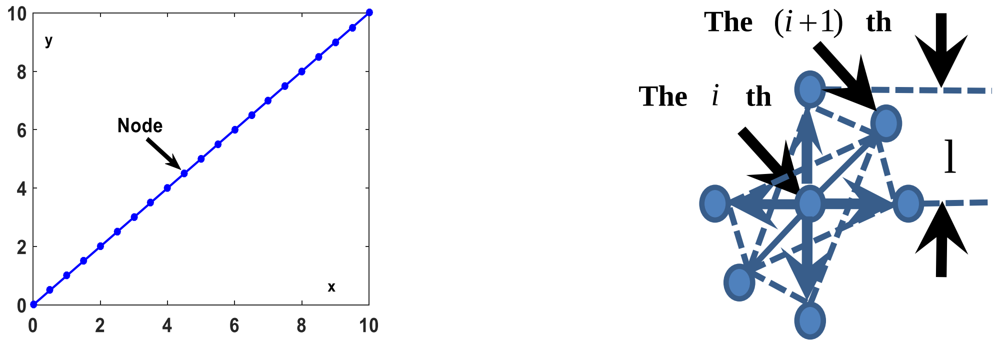
In Figure 1(b), the search step length is λ, and thus, for the i-th node, we can obtain the four search direction as follows:

$$\begin{cases} x_i^{(k+1)} = x_i^{(k)} + \lambda \cdot \cos(j \cdot \pi / 2) \\ y_i^{(k+1)} = y_i^{(k)} + \lambda \cdot \sin(j \cdot \pi / 2) \end{cases} \tag{6}$$

where the superscript $(k+1)$ denotes the $(k+1)$-th iteration, and $j = 0,1,2,3$. We link the new four nodes with the $(i-1)$-th and $(i+1)$-th nodes, and calculate their obstacle energy. According to the k-th iteration result, we can obtain the path with the minimum energy. Furthermore, in order to reduce the path search computing again, for a path with n nodes, we present the variable step length $\hat{\lambda}$.

$$\hat{\lambda} = \max(G) \cdot \lambda$$

where $G = [g_1, g_2, ..., g_n]$, $\max(\cdot)$ selects the maximum of a vector, and λ is an initial invariant step length.



(a) Initial path (b) Four-direction search

Figure 1. The initial path and four direction search

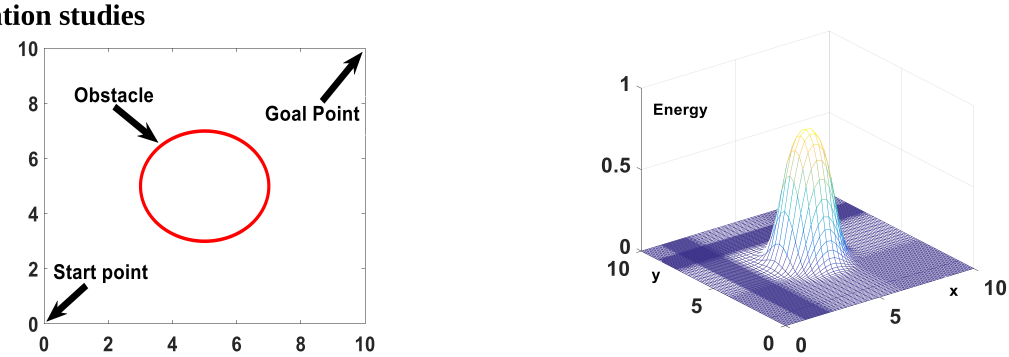
2.3. Formulation of Path Energy Function

Obviously, if we only consider the path energy, the mobile robot will move towards the place where the energy becomes as small as possible, but the final path may be very long. In order to solve this problem, we must consider the obstacle energy as well as the path energy. According to the above-mentioned discussion, we introduce the square of the difference between two adjacent nodes as the path segment energy to solve this problem.

$$L = \sum_{i=1}^{n} [(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2] \tag{7}$$

where L denotes the total path energy, and x_i and y_i denote the coordinates of i-th path-node (x_0 and y_0 denote the coordinates of start path-node).

3. Simulation studies



(a) Environmental obstacle (b) Energy profiles

Figure 2. Environmental obstacle and energy profiles

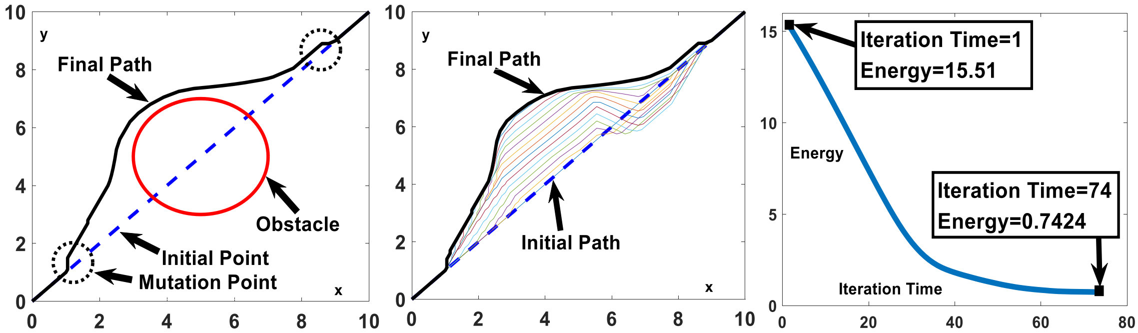
In this section, the simulation is conducted based on the presented four-direction search method with invariable step length in the static environment, and the mutation point problem arising in the simulation is discussed and improved. To enhance the performance of the four-direction search method, a variable step length is applied to reduce the iteration times and make the generation path more smooth. Finally, the four-direction method is tested in the dynamic environment. The simulations verify the effectiveness of the presented four-direction method.

3.1. Invariable search step length situation

In this subsection, obstacle-avoidance is studied and discussed with an invariant search step length for a single circular stationary obstacle.

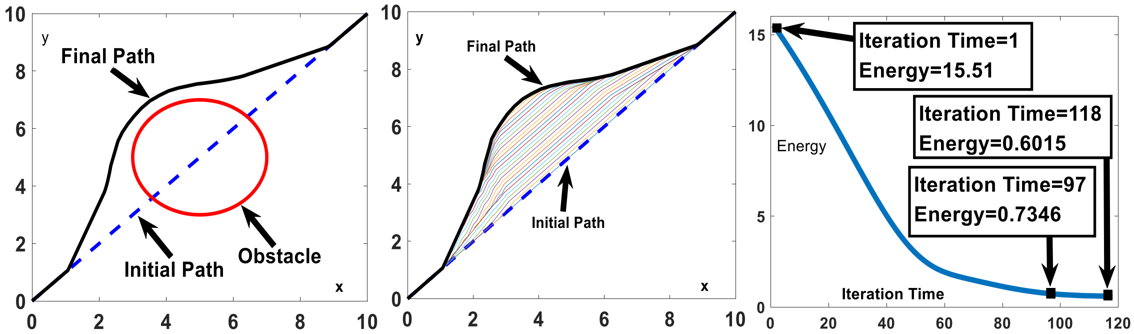
We set up a simulation environment (i.e., a planar space with $x \in [0,10]$, $y \in [0,10]$), which has a circular obstacle with {(5,5), r=2}, as shown in Figure 2(a). Moreover, the energy distribution of the obstacle is modeled and shown in Figure 2(b). According to the predefined requirements, the mobile robot requires to move from start point (0, 0) to the goal point (10, 10).

In order to make the experiment easy to discuss, we use the invariant search step length $l = 0.05$ for the four-direction scheme in the first test. The simulation results are shown in Figure 3. We can see that the final path can meet the experimental requirement. However, the final path has mutation points and is not smooth enough. Known from the simulation tests, the appearing mutation points result from the premature convergence caused by the larger search step length. In addition, the total energy (i.e., sum of the path energy and the collision energy) decreases from 15.51 of the initial path to 0.7424 of the final path, and the iteration number is 74. To improve premature convergence, we consider a smaller search step length, e.g., $\lambda = 0.03$. The corresponding simulation results are shown in Figure 4. Comparing with the final energy 0.7424 of Figure 3, the total energy has reduced to 0.7346 in the 97th iteration, and then continue converging to 0.6015, which implies that the reduced search step length can improve the phenomenon of premature convergence. In addition, with reduction of the iteration step length, the generated path is more smooth and the path mutation point is also improved. However, it is worth mentioning that the smaller step length makes the iteration times increase apparently to 118, which may decrease the computation efficacy of this scheme.



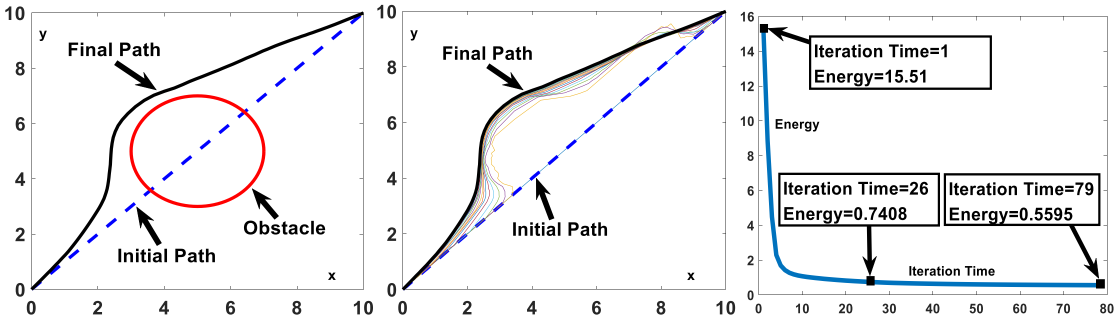
(a) Final path (b) Path profiles (c) Total energy profiles

Figure 3. Path planning and paths synthesized by FDS scheme with $l = 0.05$



(a) Final path (b) Path profiles (c) Total energy profiles

Figure 4. Path planning and paths synthesized by FDS scheme with $l = 0.03$



(a) Final path (b) Path profiles (c)Total energy profiles

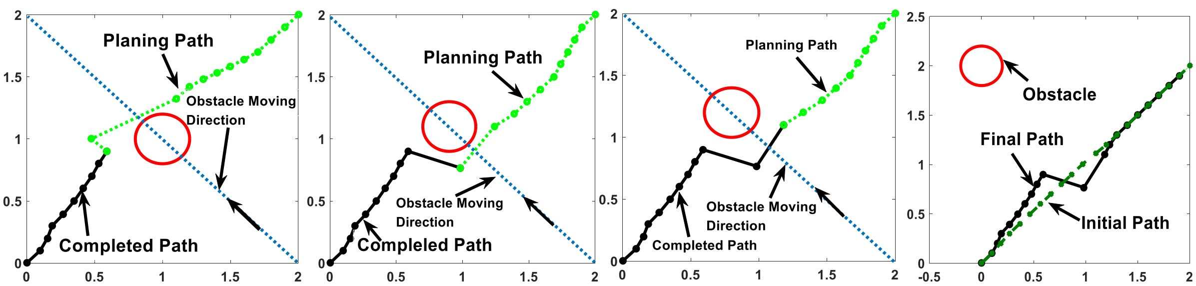
Figure 5. Path planning and Paths synthesized by FDS scheme with $\hat{\lambda} = \mathrm{Max}(G)$

3.2. Variable search step length situation

In order to take the advantages of the large step length (i.e., less iteration number) and small step length (i.e., lower total final energy), a variable search-step-length method is proposed and adopted, inspired by the above analysis and discussion. Therefore, we replace the invariant step-length with variable step-length $\hat{\lambda} = \mathrm{Max}(G) \times \lambda_0$, with λ_0 denoting the initial step length ($\lambda_0 = 1$ for this test). The simulation results are shown in Figure 5. For the comparison purpose, we can see that the total energy of the 26th iteration has been reduced to 0.7408, which is better than 0.7424 of the 74th iteration in Figure 3. Moreover, the final energy converges to 0.5595 after 79 iterations, which shows that the variable step-length method can find the optimal path with lower final energy and lower iteration number. The simulation results demonstrate the variable step-length has better performances than the invariant one, and the scheme can obtain a satisfactory solution.

3.3. Path planning in dynamic environment

Path planning in the dynamic environment is a challenging issue. Due to its real-time requirement, the FDS scheme with the variable step-length can be a feasible alternative. For the test purpose, we set up a map (i.e., a planar space with $x \in [0,2]$, $y \in [0,2]$), and a circular obstacle with {(2, 0), r=0.2} is assumed to move for the start point (2,0) to the goal point (0,2) along the diagonal straight-line path. The variable step length for the dynamic test is set as $\hat{\lambda} = \mathrm{Max}(G) \times 0.02$. The simulation results are shown in Figure 6, and corresponding iteration numbers and total energies are shown in Table 1. From Figure 6, we can see that the generated path can avoid the obstacle. For details, Figure 6(a)-(c) show the critical moments, and we can see that the mobile robot moves towards the lower-energy place, but the subsequent planning path will bypass the obstacle automatically. As a comparative result, the final path and the initial path are shown in Figure 6(d). From Table 1, we can see that the FDS scheme works well, and the total energies decrease at the critical moments. This simulation results substantiate that the proposed FDS scheme is effective for obstacle avoidance in a dynamic environment. Note that in this simulation design parameters T is set as 0.28.



(a) Node 9 (b) Node 10 (c) Node 11 (d)Initial and final paths

Figure 6. Path planning of FDS scheme for dynamic environment

Table 1. Iteration number of FDS scheme for dynamic environment.

#	Iteration number					Initial energy					Final energy				
1-5	1	104	160	173	116	0.0611	0.0991	0.1881	0.3594	0.6287	0.0611	0.0724	0.0813	0.0961	0.1535
6-10	83	33	18	12	6	0.9707	1.3137	1.568	**1.6637**	**1.5746**	0.2723	0.5111	0.8963	**1.2984**	**1.2880**
11-15	5	2	1	1	1	**1.3246**	0.9807	0.6329	0.3541	0.1727	**1.1337**	0.9541	0.6329	0.3541	0.1727
16-19	1	1	1	1		0.0753	0.0309	0.013	0.0058		0.0753	0.0309	0.0130	0.0058	

4. Conclusions

This paper focuses on the path planning method based on the neural network for collision energy building in the map, and a four-direction search method is presented and tested for the problem in the static and dynamic environment. Moreover, the proposed variable step length can improve the search performance apparently. The simulation results verify the effectiveness and practicability of the improved FDS scheme. Future work can consider to improve the generated path in the dynamic environment, and to realize proposed scheme physically.

References

[1] D. Zhu, and M. Yan, Survey on technology of mobile robot path planning, Control and Decision, 25(7), pp.961-967, 2010.

[2] Q. Zhang, B. Chen, X. Liu, and H. Yang, Ant colony optimization with improved potential field heuristic for robot path planning, Transactions of the Chinese Society for Agricultural Machinery, pp. 1-15, 2019.

[3] H. Febbo, J. Liu, P. Jayakumar, J. L. Stein, and T. Ersal, Moving obstacle avoidance for large, high-speed autonomous ground vehicles, American Control Conference, pp.5568-5573, 2017.

[4] P. Sudhakara, V. Ganapathy, B. Priyadharshini, and K. Sundaran, Obstacle avoidance and navigation planning of a wheeled mobile robot using amended artificial potential field method, Procedia Computer Science, 133, pp. 998-1004, 2018.

[5] M. Elhoseny, A. Tharwat, and A. E. Hassanien, Bezier curve based path planning in a dynamic field using modified genetic algorithm, Journal of Computational Science, 25, pp. 339-350, 2017.

[6] J. Yu, V. Kroumov, and H. Narihisa, Path planning algorithm for car-like robot and its application, Chinese Quarterly Journal of Mathematics, 17(3), pp.98-104, 2002.

[7] G. Wei, and M. Fu. An algorithm based on neural network for mobile robot path planning, Computer Simulation, 27(7), pp.112-116, 2010.

[8] K. Li, C. Yuan, J. Wang and X. Dong, Four-Direction Search Scheme of Path Planning for Mobile Agents, Robotica , doi:10.1017/S0263574719000821, pp.1-10, 2019.

[9] B. K Patle, A. Pandey, A. Jadadeesh, and D. R. Parhi, Path planning in uncertain environment by using firefly algorithm, Defence Technology, 14, pp.691-701, 2018.

[10] A. K. Guruji, H. Agarwal, and D. K. Parsediya, Time-efficient A* algorithm for robot path planning, Procedia Technology, 23, pp.144-149, 2016.

Acknowledgments

This work was supported by National Natural Science Foundation of China (NSFC) under Grant No. 61663003.