Analysis of Path Planning Algorithms for Service Robots Applied in Indoor Environments

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Abstract. Path planning technology is one of the key issues in solving mobile robot navigation technology. On the basis of traditional path planning algorithms, a large number of algorithms have been improved and applied to achieve better results, like fireworks algorithm, ant colony algorithm, A* algorithm, particle swarm algorithm, genetic algorithm, firefly algorithm, and artificial potential field method. The optimization and improvement of algorithms have made today's path planning technology more comprehensive and effectively improved the accuracy and efficiency of indoor service robot path planning. This article analyzes the development status of path planning technology for indoor environment service robot. Firstly, typical application scenarios are listed and the significance of path planning algorithms in them is introduced in combination with their application requirements. Then, some classic indoor scene path planning algorithms and improvement strategies are compared and analyzed. Finally, a summary and discussion of the above indoor environment intelligent robot path planning methods are presented.

Keywords: Mobile robot; Navigation technology; Optimization algorithms; Path planning.

1. Introduction

With the continuous development and progress of various related technologies in the field of robotics, robots are appearing more frequently in the society, and the application of robot technology has gradually shifted from the laboratory to various fields such as manufacturing, transportation, and cleaning. Autonomous indoor service robots are now widely used, such as floor cleaning robots and nursing robots. With the increasing demand for intelligence in recent years, indoor mobile robots are gradually being widely used in various application scenarios around the world [1].

Path planning, as a very important navigation technology for mobile robots, is crucial for any non-remote-controlled mobile robot. In relatively small and enclosed indoor spaces, good path planning technology is especially important to ensure that robots can move along predetermined trajectories and complete the tasks they are supposed to undertake. Different application scenarios also require different path planning algorithms to meet the special needs of indoor service robots.

This article provides an overview and analysis of various path planning algorithms for indoor service robots. Firstly, the typical application scenarios of indoor wheeled service robot path planning technology are analyzed. Then, some mainstream path planning algorithms are compared and analyzed. Finally, a summary and outlook on indoor service robots are presented.

2. Overview of typical application scenarios

2.1. Restaurant environment

In the service industry, the cost of food service personnel is better than the cost generated by mobile robots. Therefore, with the maturity and progress of robot-related technologies, more and more restaurants are beginning to use service robots to act as waiters. Robot systems designed based on ROS and SLAM have almost verified their feasibility in restaurants, and can fully realize the function of transporting food from the service point to the corresponding table [2].

2.2. Home enviorment

Currently, many countries around the world are experiencing a common phenomenon of aging populations, and in some countries, this phenomenon has a serious impact. The use of mobile service robots to assist with household chores is considered a feasible solution. By designing autonomous robot systems specifically for household organization, indoor cleaning tasks can be accomplished [3].

2.3. Agricultural enviorment

With the continuous advancement of rural urbanization, the agricultural labor force is gradually decreasing, and agricultural robots have gradually begun to play an important role in the agricultural field. Agricultural robots can not only replace labor more perfectly in sowing seeds, plant processing, harvesting and other links, but also have higher accuracy and efficiency. With the continuous development of agricultural robot systems, it can be found that the average harvest success rate of crops has increased, the average harvest cycle has decreased, and both have reached a considerable proportion [4].

3. Comparative analysis of path planning algorithms

3.1. Ant colony algorithm

3.1.1 Classical ant colony algorithm

Ants will choose the shortest path through the hormones released by themselves. Ant colony algorithm is a simulation algorithm based on the moving behavior of ants on the road surface. The two key steps of ant colony algorithm are routing rules and pheromone updating. The traditional ant colony algorithm state transition rules are shown as follows:

$$p_{ij}^{\mathrm{m}} = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}\cdot[\eta_{ij}(t)]^{\beta}}{\sum_{j\in \text{ allowed }_{\mathrm{m}}}[\tau_{ij|}(t)]^{\alpha}\cdot[\eta_{ij}(t)]^{\beta}}, & j \in \text{ allowed }_{\mathrm{m}} \\ 0, & j \notin \text{ allowed }_{\mathrm{m}} \end{cases} \quad (1)$$

$$\eta_{ij}(t) = \frac{1}{d_{ij}}$$

Where ρ_{ij}^{m} is the probability of ant m from node i transfer to node j at time t; $\tau_{ij}(t)$ represents the pheromone content of path (i,j) at time t; $\eta_{ij}(t)$ is the heuristic information of path (i,j) at time t; α is pheromone heuristic factor; β is expected heuristic factor; $allowed_m$ is the optional next path set; d_{ij} is the distant of path (i,j). The traditional ant colony algorithm pheromone update rules are as follows:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij}(t) \quad (2)$$

Where $\tau_{ij}(t+1)$ represents the updated pheromone; ρ is pheromone volatility coefficient; $(1-\rho)$ is pheromone residue factor; $\Delta\tau_{ij}(t)^{k}$ is the pheromones that ant k left behind at the path (i,j). The expression is shown below:

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{M} \Delta\tau_{ij}(t)^{k} \quad (3)$$

Where $\Delta\tau_{ij}(t)$is pheromone increment at time t,namely the pheromones that ant k left behind at the path (i,j)in the path; Q is a constant for the pheromone intensity, L_k as the total length of path in ant k in this cycle.

$$\Delta\tau_{ij}(t) = \begin{cases} \frac{Q}{L_k}, & \text{ant pass through the path } (i,j); \\ 0, & \text{ant do not pass through the path } (i,j) \end{cases} \quad (4)$$

Ant colony algorithm has strong searching ability and is easy to be combined with other path planning algorithms. However, traditional ant colony algorithm has some defects in path planning of mobile robots, such as slow convergence speed, easy to fall into local optimal solution and unreasonable initial pheromone allocation [5]. Therefore, many scholars have put forward a lot of improved ant colony algorithms after a lot of research. The following is only a brief description of some improved algorithms.

3.1.2 Ant colony algorithm with A* algorithm

This algorithm combines the A* algorithm with the improved ant colony algorithm. Firstly, a raster map is established, in Fig.1, black is passable position and white is inaccessible position.

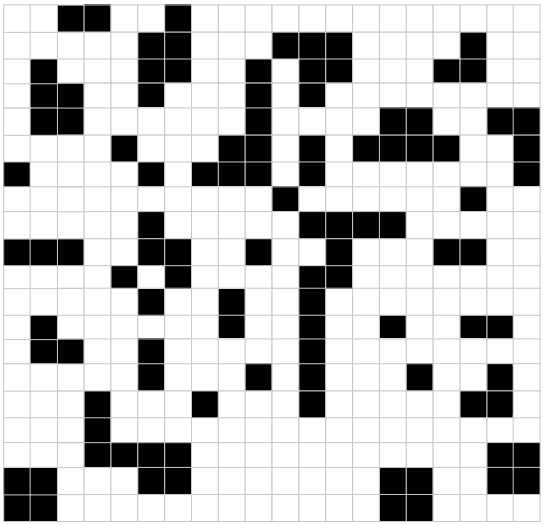


Fig. 1 Raster map

Then, a corner heuristic function is established:

$$\omega_{ij}(t) = \mathrm{e}^{-a}$$
$$a = \begin{cases} 1, \theta = 45^\circ \\ 2, \theta = 0^\circ \text{ or } 90^\circ \\ 3, \theta = 135^\circ \end{cases} \tag{5}$$

The $w_{ij}(t)$ is the current node to the next node corner stimulating factor, a said turning Angle size choices affect the value of the path to an ant. The improved distance heuristic function is:

$$\eta_{ij} = \frac{1}{\mu d_{ij} + \frac{\sigma}{\mu} d_{je}} \tag{6}$$

Where μ is the distance factor; μ is a constant, and can be change according to actual condition, d_{je} is the next node to the end point of straight-line distance. The corresponding optimized algorithm flowchart is shown below:

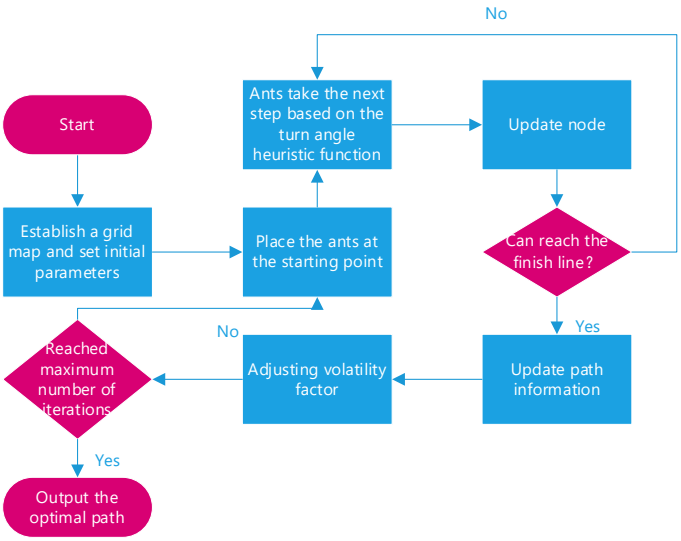


Fig. 2 Improved flow chart

Based on the above improvements to the ant colony algorithm, the convergence rate can be improved to avoid falling into the local optimal solution [6].

3.1.3 Ant colony algorithm based on direction guidance

This method improves the ant transfer probability, and proposes a new heuristic information calculation method, which uses the interpolation strategy for path smoothing optimization. The new heuristic information calculation method is shown below:

$$\begin{gathered} \eta = [\eta_{ij}]^{\beta} \cdot e^{\cos\theta} \\ \theta = \arccos V \\ V = \frac{(x_k - x_i)(x_G - x_i) + (y_k - y_i)(y_G - y_i)}{\sqrt{(x_k - x_i)^2 (y_k - y_i)^2}\sqrt{(x_G - x_i)^2 (y_G - y_i)^2}} \end{gathered} \tag{7}$$

Where θ is the Angle between the current node and the target node and the next optional node; (x_i, y_i) indicates the coordinates of the current node; (x_k, y_k) indicates the neighborhood node coordinates; (x_G, y_G) indicates the coordinates of the target node; $e^{cos\,\theta}$ is guidance function, $\theta \in [0, \pi]$.The transfer probability of improved ant colony algorithm:

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}(t)]^{\beta} \cdot e^{\cos\theta}}{\sum_{s \in J_k(i)} [\tau_{is}(t)]^{\alpha} \cdot [\eta_{is}]^{\beta} \cdot e^{\cos\theta}} & \text{when} j \in J_k(i) \\ 0 & \text{else} \end{cases} \tag{8}$$

Where $\tau_{ij}(t)$ represents the pheromone intensity on the path (i, j), $\eta_{ij}(t)$ is the heuristic information value, α is the pheromone heuristic factor, β is the expected heuristic factor, and $J_k(i)$ is the set of nodes that ant k is allowed to choose for its next step. The insertion strategy can be used to optimize the shortest path between any two points. Suppose A→B→C→D is the original path length, with A being the starting point. Moving along the path A→B→D, if a node C is found on this path, connecting A and C forms the path A→C, and replacing the path A→B→C creates a new path. When node D is found, assuming there is an obstacle between A and D, a direct path between A and D cannot be formed. Therefore, the new path A→C→D is generated, which has a shorter path length than A→B→D, forming a new optimized path. The principle is illustrated in Fig 3.

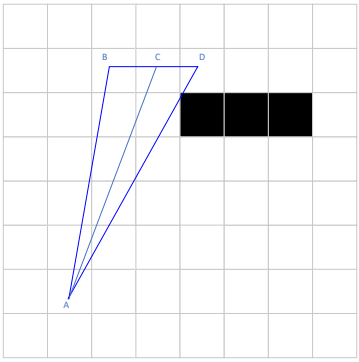


Fig. 3 Schematic diagram of the insertion strategy

The steps of path smoothing optimization are shown in Fig. 4, where the paths generated before optimization are represented by red dashed lines, and the paths after optimization are represented by blue solid lines.

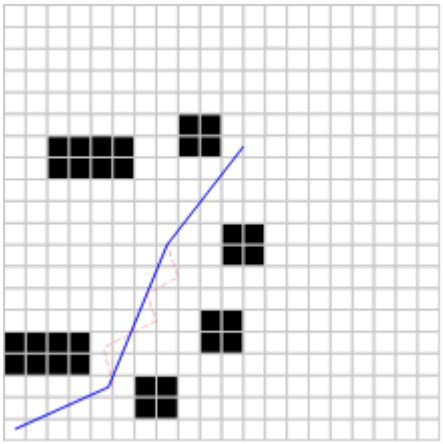


Fig. 4 Schematic diagram of path smoothing optimization steps

The improved algorithm is shown in Fig. 5:

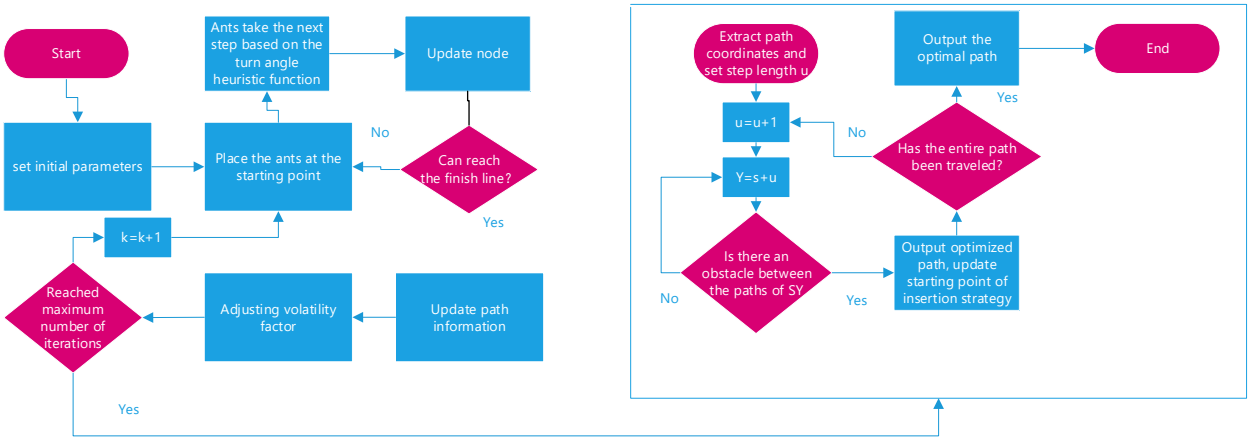


Fig. 5 Improved algorithm flow chart

The average convergence times, average fold points of paths and average path length of this algorithm have been significantly reduced [7].

3.2. Fireworks algorithm

Fireworks algorithm (FWA) is a new swarm intelligence algorithm proposed to find the optimal solution by simulating the firework explosion spark generation process. One advantage of this algorithm over other algorithms is that it performs better when dealing with complex problems.

3.2.1 Classical Fireworks Algorithm

In the algorithm, fireworks are used as a viable solution to optimize space problems. Think of the sparks generated when fireworks explode as the process of neighborhood search. As a population and evolution-based swarm intelligence algorithm, FWA has similarities with other algorithms. The best solution is generated through multiple iterations. At each iteration, fireworks undergo explosive action, Gaussian manipulation, mapping principles, and selection strategies to form a new generation of fireworks. Finally, the whole gradually tends to the optimal solution. A key part of FWA is the explosive action, which mimics the behavior of natural fireworks explosions in the sky. Explosion amplitude calculation formula is shown as follow.

$$A_i = \hat{A}\frac{f(x_i)-y_{min}+\varepsilon}{\sum_{i=1}^{n}(f(x_i)-y_{min})+\varepsilon} \tag{9}$$

Spark count calculation formula is shown as follow.

$$s_i = m_s\frac{y_{max}-f(x_i)+\varepsilon}{\sum_{i=1}^{n}(y_{max}-f(x_i))+\varepsilon} \tag{10}$$

Where $f(x_i)$ is firework's function value, and m_s and $\hat{A}$ are constant, and they are used to control the the number of sparks and the magnitude of the explosion. The boundary of the spark count is defined as:

$$s_i = \begin{cases} \text{roun d}(am_s), & \text{if } s_i < am_s \\ \text{roun d}(bm_s), & \text{if } s_i > bm_s, a < b < 1 \\ \text{roun d}(s_i), & \text{otherwise} \end{cases} \tag{11}$$

Where constants a and b are used to adjust the extreme value of the sparks.

3.2.2 Discrete fireworks algorithm

The basic fireworks algorithm is mainly applied to the continuous optimization problem, but when solving discrete problems, the algorithm is difficult to play a direct role. So, it is necessary to improve a discrete fireworks algorithm. Because the solution obtained by the discrete fireworks algorithm does not cross the bounds of the path planning problem, the mapping rule is removed. The adjusted algorithm structure is shown below.

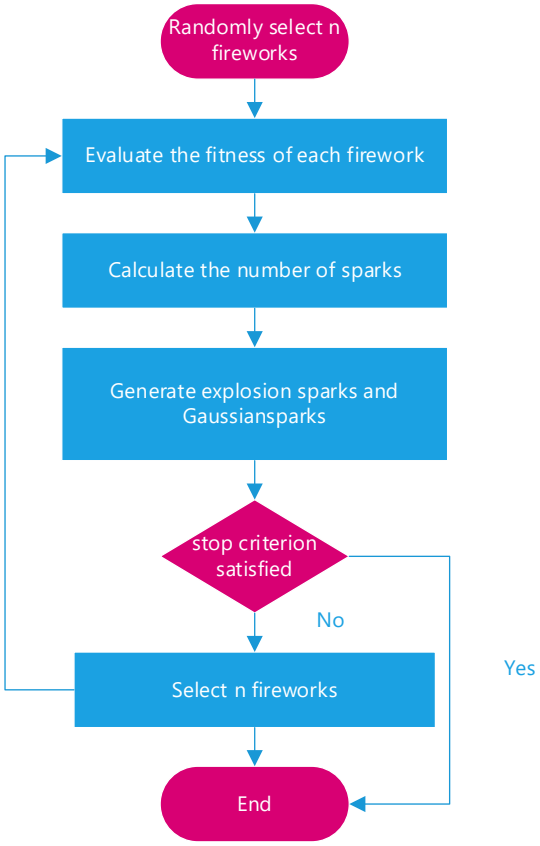


Fig. 6 Improved algorithm flow chart

Improve the explosion operator, then modify the Gaussian spark generation and change the selection mechanism. Through simulation experiments, it is found that the discrete method of fireworks algorithm will have more scenarios to apply [8].

3.2.3 Improved fireworks algorithm based on guidance factor

The method introduces dynamic explosion range, and the specific calculation expression is as follows:

$$s_i = \begin{cases} A_i^1 & g = 1 \\ R_1 A_I^{g-1} & f(x_i^g) \geqslant f(x_i^{g-1}) \\ R_2 A_I^{g-1} & f(x_i^g) < f(x_i^{g-1}) \end{cases} \tag{12}$$

In this case, g is the current iteration number; R1 and R2 are constant parameters that control the explosion radius, where R1 has a value range of (0, 1), and R2 is a number greater than 1.

A guiding factor is proposed to direct the fireworks to update their positions. The three individuals with the highest fitness values are designated as L1, L2, and L3, which guide other fireworks in the search. The remaining fireworks are defined as L4. The level of L4 is lower than that of the other three categories. This is illustrated in Fig 7.

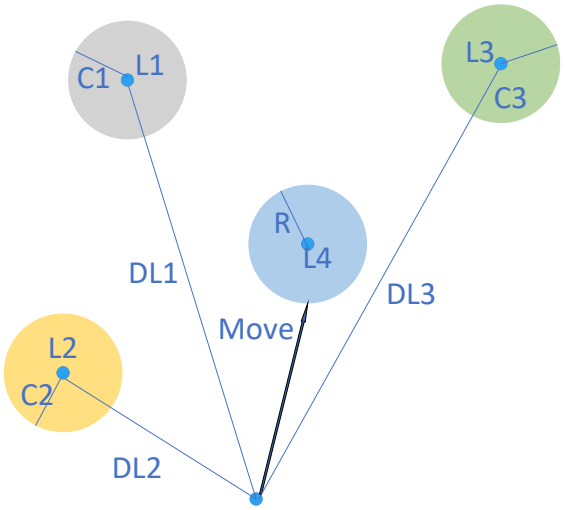


Fig. 7 Guiding factor directing fireworks

Gaussian variation is used in the basic fireworks algorithm, but overlap is easy to occur in the variation process, resulting in the algorithm falling into the optimal near the starting point. Therefore, a free variation strategy is proposed. The expression is as follows:

$$x_{i,j} = \left(x_{w,j} - x_{b,j}\right)x_{w,j}\text{ran d}(0,1) \tag{13}$$

Where $x_{b,j}$, and $x_{w,j}$ indicate the positions of the current optimal and worst fireworks in the j dimension, respectively. $\text{ran d}(0,1)$ represents random numbers evenly distributed across the interval $[0,1]$. The algorithm proposes a competitive learning strategy, in which the individual fitness value will approach the best fireworks through learning, thus improving the algorithm's local search performance around the dominant fireworks and improving the convergence speed. The expression is as follows:

$$x_i^g = \begin{cases} (1-\gamma)x_i^g + \gamma x_b^g & x_i^g < x_i^{g-1} \\ x_i^g & \text{others} \end{cases} \tag{14}$$

Where x_i^g is the i-th candidate firework; x_b^g is the best firework among the candidate individuals; g represents the current iteration number; γ is a constant. After simulation, it can be observed that the improved fireworks algorithm corresponds to a shorter path planning length, fewer inflection points, and higher convergence efficiency [9].

3.3. Artificial potential field method

3.3.1 Traditional artificial potential field method

In traditional artificial potential field method, controlled objects move in particle motion and move in plane motion in two-dimensional space. The principle of this algorithm is simple and easy to understand, with high accuracy and real-time performance. A virtual artificial potential field is used. The virtual potential field in the whole environment is mainly abstracted into gravitational potential field and repulsive potential field, which are collectively called the entire virtual environmental potential field. Objects move in the potential field, and the direction of motion is the direction of potential energy decline:

$$U_{att}(q) = \frac{1}{2}k_{att}\rho^2\left(q, q_{\text{gaal}}\right) \tag{15}$$

Where k_{att} represents attractive potential field gain coefficient, which can be adjusted according to specific conditions; q is current position; q_{goal} is garget position;$\rho\left(q, q_{goal}\right)$ is Euclidean distance, denoted as$\left|q - q_{goal}\right|$. The mathematical function of the repulsive potential field can be expressed as:

$$U_{rep}(q)=\begin{cases}\frac{1}{2}k_{rpp}\left[\frac{1}{\rho(q,q_0)}-\frac{1}{\rho_0}\right]^2, & 0\leqslant\rho(q,q_0)<\rho_0\\ 0 & \rho(q,q_0)\geqslant\rho_0\end{cases} \tag{16}$$

Where k_{rpp} represents repulsive potential field gain coefficient, which can be adjusted according to specific conditions; q_0 is the location of the obstacles $\rho(q,q_0)$ is Euler distance, denoted as $|q-q_0|$; and ρ_0 is a constant value, representing the degree to which the obstacle affects the object. Through the description of the traditional artificial potential field method, a problem has been found, that is, its adaptability to dynamic environments is relatively low. Many algorithms that improve upon the traditional artificial potential field method are designed to address this issue.

3.3.2 Improved artificial potential field method based on local minimum problem and target unreachable problem

When the sensor determines that the obstacle avoidance is in the local minimum problem, it adopts the way of setting the virtual target point to avoid the obstacle, then adopts the right turn avoidance method, right turn $\frac{\pi}{3}$ as the deflection Angle, using step length ρ_0 as the deflection distance, the coordinate position of the virtual target point is shown as follows:

$$\begin{cases}x_g=x_0+\rho_0\cos\ \alpha_g\\ y_g=y_0+\rho_0\sin\ \alpha_g\end{cases} \tag{17}$$

Where x_0, y_0 are the current coordinate position of the object,; a_g=a_{att}+ π/ 3,a_{att} is the current gravitational Angle.This method can escape the local optimal, reach the virtual target point, and then switch the route to the original target point, so as to solve the local minimum problem.When the object is close to the target minimum point, the gravity will become smaller and smaller, and the repulsive force will become larger and larger, so that the phenomenon of failing to reach the target point will appear. In order to solve this problem, the relative distance between the object and the target point is introduced into the repulsive potential field function, so as to reduce the repulsive effect of obstacles near the target point on the underwater vehicle. The mathematical function of the repulsive potential field is shown in the following equation:

$$U_{re\rho}(q)=\begin{cases}\frac{1}{2}k_{rep}\left[\frac{1}{\rho(q,q_0)}-\frac{1}{\rho_0}\right]^2\rho^n(q,q_{goal}) & 0\leq\rho(q,q_0)<\rho_0\\ 0 & \rho(q,q_0)\geq\rho_0\end{cases} \tag{18}$$

Where q is current position; q_{goal} is garget position; $\rho(q,q_{goal})$ is Euler distance, denoted as $|q-q_{goal}|$. Simulation results show that the algorithm has good local path planning effects under relatively ideal conditions [10].

4. Conclusion

In this paper, some application scenarios of indoor mobile service robots are listed, and a very important technical path planning of mobile robots is emphatically analyzed and discussed. This paper also compares and discusses some current mainstream path analysis and planning algorithms. On the basis of traditional algorithms, many improved path planning algorithms have well solved some problems existing in path planning technology, and have a significant improvement in various indicators. For example, the improved ant colony algorithm has stronger direction planning in path planning, which can have higher accuracy and efficiency in restaurant delivery. Using discrete fireworks algorithm can greatly enhance the application of service robot in home environment. It is foreseeable that with the development of robot-related technologies, such as the path planning technology mentioned in this paper, indoor service robots will be more widely used and play an important role in various fields such as family, catering, transportation and medical treatment. It is even expected to become as integral a part of people's lives as smartphones and mobile payments.

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