Research on path planning of intelligent shopping cart in large shopping mall

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Abstract: The recovery and arrangement of shopping carts in large shopping malls need to invest a lot of manpower and financial resources, and its recovery efficiency is low. In order to achieve the purpose of self-driving and collision free recovery of shopping cart near work, an improved algorithm is proposed. The basic RRT algorithm takes the starting point of the intelligent shopping cart as the root node and adds the gravity component of the artificial potential field, and sets the node selection range, which overcomes the randomness of the random tree growth. The simulation experiments show that the improved algorithm has the characteristics of high obstacle avoidance, short search time and strong real-time.

Key words: Path planning; rapidly-exploring random tree; Intelligent shopping cart

1 INTRODUCTION

There are many kinds of goods in shopping malls, which occupy a large area. In the coming hours, professional staff should be organized to reclaim the shopping carts and waste a lot of money. Therefore, it is important to study the recycling of intelligent shopping carts. Path planning has been widely studied by different researches in order to give the autonomous robot the ability to navigate in complex or dynamic environments in a safe manner avoiding collision with obstacles.

At present, rapidly-exploring random tree (RRT) algorithm based on sampling is widely used. RRT algorithm is the starting point as the root node, through a finite number of random sampling, increase leaf node, generate a random spanning tree, when the leaf nodes in random trees to reach the target or target area, then it is possible to find an optimal or suboptimal collision free path from the initial node to the target point in the random tree. Compared with other path planning methods, the algorithm reduces the expected distance between random points and extended trees in incremental form and does not need to model the environment. It solves the difficult situation of modeling in complex environment. But because of its randomness, it also brings some shortcomings, such as exploring tree growth direction is random and long search time, etc. In this paper, an improved RRT algorithm is proposed to solve the problem of slow convergence of RRT algorithm. By introducing the artificial potential field method, the gravitational component is added to guide the smart shopping cart to move toward the target point. When selecting nodes, the selection range of nodes is increased and the randomness of node selection is reduced, and the convergence speed of the algorithm is accelerated.

2 DESCRIPTION OF PATH PLANNING

In order to improve the accuracy of path planning, in this paper, the RRT algorithm is further optimized. The working environment of intelligent shopping cart is limited in two dimensions. According to the degree of mastering the environment, the path planning of mobile robot can be divided into the global path planning with fully known environment and the local path planning with unknown or incompletely known environment.

Path planning can be briefly described as shown in Fig.1, the black circles represent obstacles x_{obs}, X is a complex environment with obstacles, x_{init} is the starting point of the mobile robot, x_{obs} is the target point of mobile robot, curve representation in the obstacle region, the mobile robot can find a collision free optimal path from the starting point x_{init} to the target point x_{goal}.

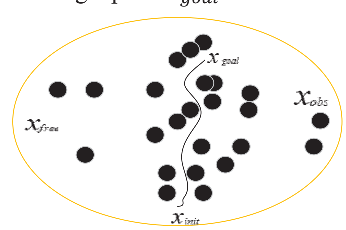

Fig. 1 Diagram of path planning

3 RRT ALGORITHM

3.1 Basic RRT algorithm

The path planning in two-dimensional state space means that in the given state space Z, the intelligent shopping cart starts from the starting point z_{init} to the target point z_{goal} or the target area to plan a collision free path. In avoid the obstacle or dangerous area z_{obs}, that is to say, it should always be in the safe area z_{free}. The z_{obs} and z_{free} are complementary, which together form the state space Z of the intelligent shopping cart.

The basic RRT algorithm is in the state space in z_{free} region is extended to generate random tree T_k, the basic idea is as follows: firstly, the starting point z_{init} was taken into the extended random tree as the root node, in the region of the z_{free}, a random node z_{rand} is generated and the node z_{near} is found to make it the shortest distance from the z_{rand} .That is, the geometric distance between z_{near} and z_{rand} satisfies the formula $D(z_{near}, z_{rand}) \leq D(z, z_{rand})$,(Z is a set of nodes in T_k) and then seek the new node $z_{new} \in Z$ of the $D(z_{near}, z_{new}) = \rho$ in the direction of the connection between z_{near} and z_{rand}, among them, ρ is the search tree growth step and $\rho > 0$. It is judged whether the nodes on the connection between z_{new}, z_{near} and z_{new} are in conflict with obstacles. If there is a conflict, the current node will be abandoned and reselect the z_{rand} node. Then finding z_{near} nodes and conflicting judgments should be repeated. if it does not conflict with the obstacle, the z_{new} node is added to the extended random tree in T_k, the formation of T_{k+1}, by repeating the process continuously , random point and the new child node are produced, until the new generation node meets $D(z_{new}, z_{goal} < \rho)$ and the nodes on the connection between z_{new} and z_{goal} are in the security zone z_{free}, then z_{goal} is added to the random tree, and the expansion of the random tree is successful.

3.2 Improved algorithm analysis

3.2.1 Increase target gravity

In order to improve the randomness in the algorithm, the objective function in the algorithm to increase the gravity based on the gravitational potential field method, the path planning is always toward the target expansion, so as to avoid the local minimum value to improve the accuracy of the algorithm. The increase of target gravity in extended random tree is as follows Fig.2:

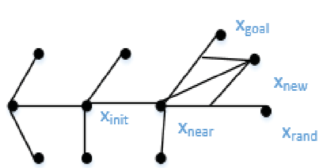

Fig.2 Introducing target gravity to construct random tree

As shown in Fig.2, x_{init} is the starting point of random spanning tree, x_{rand} is a randomly generated node, x_{goal} is the target node, and x_{new} is the introduced target node. In the extended random tree planning path, introducing the object to make it continuously after gravity order to ensure safety, the intelligent shopping cart should toward the target direction of planning, the improved algorithm can make the path planning not only reduces the search time, random search, and to a certain extent, the amount of calculation is greatly reduced.

The specific steps of algorithm improvement are as follows: Suppose the smart shopping cart is the location of the current x ,every node into a target gravitational functiong(n), $n$represents a node here extended outward from the starting point, with the function can be described as the following formula (1):

$$f(n) = g(n) + h(n) \tag{1}$$

In formula (1), $f(n)$ represents the growth instruction function from node n to target point, $g(n)$ is the introduced objective function, and $h(n)$ is the random growth function from the starting point to the node n.

Gravitational potential energy function:

$$u_x = \frac{1}{2} k_p \| x_{goal} - x_{near} \|^2 \tag{2}$$

The gravitational function of the target point and the nearest node:

$$G_x = k_p \| x_{goal} - x_{near} \| \tag{3}$$

Among them, the gravitational field coefficient is k_p, x_{goal} is the robot's target position, and $\|x_{goal} - x_{near}\|$ is the absolute value of the geometric distance between the node x_{near} and the target point x_{goal}.

From the above formula can construct the objective function of gravity $g(n)$and we can get formula (4):

$$g(n) = \frac{k_p (x_{goal} - x_{near})}{\| x_{goal} - x_{near} \|} \tag{4}$$

On the basis of the RRT algorithm, the new leaf node is added, and the gravitational function of the target will calculate the gravity of each node to the target, thereby affecting the selection of nodes, and then guiding the random number to grow in the direction of the target.

The random growth function $h(n)$is obtained after adding the new leaf node x_{new} then We can get formula (5).

$$h(n) = \frac{\rho (x_{goal} - x_{near})}{\| x_{rand} - x_{new} \|} \tag{5}$$

Therefore, the improved calculation formula of the new blade node, we can get formula (6).

$$x_{new} = x_{near} + h(n) + g(n) \tag{6}$$

The g(n)and h(n) were substituted into the formula (7).

$$x_{new} = x_{near} + \frac{\rho (x_{goal} - x_{near})}{\| x_{rand} - x_{new} \|} + \frac{k_p \rho (x_{goal} - x_{near})}{\| x_{goal} - x_{near} \|} \tag{7}$$

The objective gravity function $g(n)$ has a great influence on the growth of the spanning tree. The value of the coefficient $k$determines whether the path of the extended tree programming is optimal. If the gravity coefficient k value is too large, the growth of the tree cannot completely avoid obstacles, path planning is not optimal; if the coefficient k value is too small, although it can avoid obstacles but will increase the randomness of new leaf node selection. Therefore, the gravitational coefficient k plays an important role in the optimization of the path. Many times, of repeated tests, finally set up an optimum value, not only to ensure a good robot to avoid obstacles, but also can reduce the randomness of path planning, which points toward the goal of outward expansion, thus plan out an optimal path.

3.2.2 Optimization of RRT algorithm

The basic RRT algorithm is directly judgment whether there are obstacles with the node z_{new} and the line of z_{new} and z_{near} , if there is no obstacles，then the node will be added to the random tree as a parent node in this iteration, This leads to the generation of unnecessary nodes in the local area, which cannot be closer to the optimal solution. Thus, improving RRT algorithm considers all nodes in a neighborhood of z_{new} and evaluates the cost of choosing each as the parent. This process evaluates the total cost as the additive combination of the cost associated with reaching the potential parent node and the cost of the trajectory to z_{new} .The node that yields the lowest cost becomes the parent as the new node is added to the tree. Repeat the above process of selecting z_{new} and proceed to the next cycle, until the new node is found in the state space, the search is ended when the target is within the target range or the target node. An improved RRT algorithm is described as follows:

Aglorithm 1 : $T = (V, E) \leftarrow RRT^*(z_{init})$
1. $T \leftarrow InitilizeTree();$
2. $T \leftarrow insretNode(\phi, z_{init}, T);$
3. $for\ i = 1\ to\ i = K;$
4. $z_{rand} \leftarrow Sample(i);$
5. $z_{nearest} \leftarrow Nearest(T, z_{rand});$
6. $(x_{new}, u_{new}, T_{new}) \leftarrow steer(z_{nearest}, z_{rand});$
7. $if\ ObstacleFree(x_{new});$
8. $z_{near} \leftarrow Near(T, z_{new}, |V|);$
9. $z_{min} \leftarrow ChooseParent(z_{near}, z_{nearest}, z_{new}, x_{new});$
10. $T \leftarrow InsertNode(z_{min}, z_{new}, T);$
11. $T \leftarrow Rewire(T, z_{near}, z_{min}, z_{new});$
12. $Return\ T$

Aglorithm 2 : $z_{min} \leftarrow ChooseParent(z_{near}, z_{nearest}, x_{new})$
1. $z_{min} \leftarrow z_{nearest};$
2. $c_{min} \leftarrow cost(z_{nearest}) + c(x_{new});$
3. $for\ z_{near} \in Z_{near}$
4. $(x', u', T') \leftarrow steer(z_{near}, z_{new});$
5. $if\ obstacleFree(x')\ and\ x'(T') = z_{new}$
6. $c' = cost(z_{near}) + c(x');$
7. $if\ c' < cost(z_{new})\ and\ c' < c_{min}$
8. $z_{min} \leftarrow z_{near};$
9. $c_{min} \leftarrow c';$
10. $return\ z_{min}$

Aglorithm 3 : $T \leftarrow Rewire(T, z_{near}, z_{min}, z_{new})$
1. $for\ z_{near} \in Z_{near} \setminus \{z_{min}\}$
2. $(x', u', T') \leftarrow steer(z_{new}, z_{near});$
3. $if\ obstacleFree(x')\ and\ x'(T') = z_{near}\ and$
$cost(z_{new}) + c(x') < cost(z_{near})$
4. $T \leftarrow reconnect(z_{new}, z_{near}, T);$
5. $return\ T$

4 SIMULATION EXPERIMENT

4.1 Experiment simulation of basic RRT algorithm

Fig.3(a) is planning results MATLAB static simulation map, the size of map is 140*140, the black solid circle indicates the number of random obstacles generated, the coordinates of the starting point coordinates and the target point that intelligent shopping cart respectively (10,10), (130,130). The blue line represents the direction of the growth of RRT in limited obstacle, red thick lines in the diagram in the obstacle intelligent shopping cart autonomous planning the best route map results. After a lot of experiments and simulation, when the search step size is too large, although to some extent reduce the number of nodes in path needed but increases the probability of nodes encountered obstacles in the propagation process, the smaller the search step will make the number of nodes in the expanding process of the increase, reduce the node searching efficiency. Experiments show that the optimal path length is 5 or 6, the path can not only effectively avoid obstacles, but also has the highest path planning efficiency, so the random tree search step size is 6.

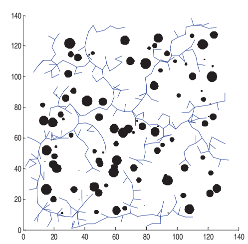

Fig.3(a) static simulation graphical interface

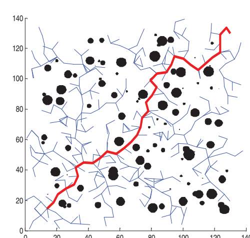

Fig.3(b)Basic RRT algorithm

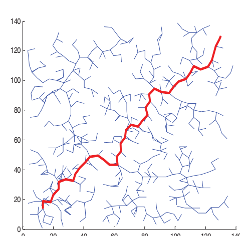

Fig.3(c) Path planning without obstacles

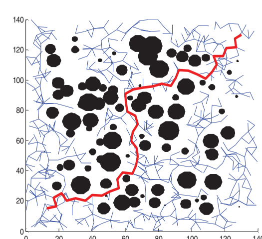

Fig. 3(d)Path planning of 100 obstacles

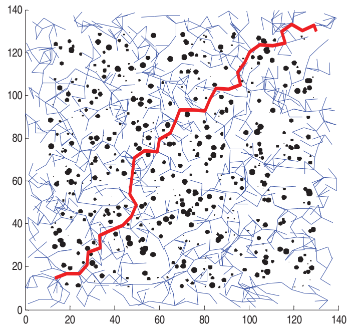

Fig.3(e)Path planning of 500 obstacles
Fig. 3 simulation results of basic RRT algorithm

Fig.3(a)(b) are in random obstacles during the formation of the static simulation interface and the basic RRT algorithm for path planning results, from the fig.3 can be seen a large number of nodes needed in path planning, strong random tree growth direction. Fig.3(c) is the path that is planned for an intelligent shopping cart without obstacles. Fig.3 (d)(e) is the best path result map that is independently planned when the obstacles are 100 and 500. As can be seen from Fig.3, the basic rapidly exploring random tree (RRT) algorithm can plan a collision free path from the start- ing point to the target point when obstacles are more intensive, however the path planned need a large number of nodes, random tree generation direction randomicity, which it makes the convergence of the planning path slower.

4.2 Improved RRT algorithm experiment simulation

In view of the rapidly-exploring random tree growth in the process of randomness, convergence speed and other shortcomings to improve, as shown in Fig.4. In order to make the improved algorithm more convincing, the data used in Fig.4 is consistent with the basic RRT algorithm data. From the simulation results of Fig.4, we can see that the improved RRT algorithm greatly reduces the number of nodes in the same environment and improves the direction of the search tree obviously.

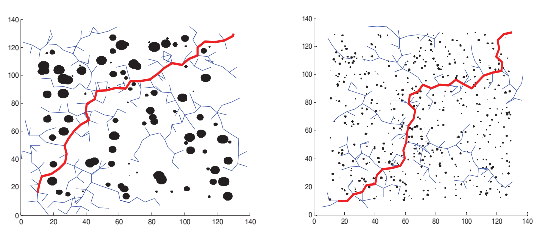

Fig.4(a) improved planning results of 100 obstacles

Fig.4(b) improved planning results of 500 obstacles

Fig.4 improved RRT algorithm simulation results

Compared with the basic RRT algorithm, the improved RRT algorithm accelerates the convergence speed and reduces the randomness of random tree growth. The results show that the algorithm is suitable for autonomous recovery of smart shopping cart in large shopping malls.

5 CONCLUSIONS

In order to verify the feasibility of the rapidly-exploring random tree algorithm in the autonomous recovery of intelligent shopping cart, a large number of experiments were carried out. The experimental results show that the improved algorithm has a strong obstacle avoidance ability, regardless of the density of obstacles, the algorithm can reach the target point at the fastest convergence speed. Therefore, the algorithm is feasible for complex environments such as large shopping malls.

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