A Route Planning Algorithm for Ball Picking Robot with Maximum Efficiency

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***Abstract* — In this paper, the author develops a route planning algorithm for ball picking robot with maximum efficiency. A simplified visibility graph suitable for path planning algorithm of mobile robot is proposed to solve the problem of environment modeling. Considering the position of the obstacles in the environment and the relationship between starting and end points of the mobile robot, the obstacles which do not affect the result of path planning are declared redundant and removed, thus the representation of the environment model is simplified. The purpose of reducing the number of alternative paths in the process of path planning is achieved, which improves the efficiency of the follow-up path planning algorithm.**

Keywords - picking up ball route, planning algorithm, ball picking robot, efficiency.

I. INTRODUCTION

Mobile robotics is a major application of cutting-edge technology. Related technologies in the mobile robot research, path planning is an important part of the study and issues among all of the robotics researches. The chief task of the path-planning is: when the mobile robot is running under the environment space with obstacle it is usually asked to seek one of optimal path which would link between the start point and the end point, and make sure in the motion of this process, mobile robot can pass all obstacle in safe and collision-free.

In Chiu's paper [1], PSO is realized by the organic social behaviors instead of the mechanism of natural selection in Evolutionary Computation, and by the cooperation and competition among the individuals themselves to search the optimum of the problem. PSO has been widely applied in image processing, pattern recognition, operational research and so on due to its simple concept, simplicity of implementation, less parameters to control and rapid convergence speed. However, it has proved that PSO does not satisfy the requirements of a global search algorithm and PSO cannot guarantee to converge on the global minimum. Aiming at the fatal limitation, keeping to the philosophy of PSO algorithm, the Quantum-behaved Particle Swarm Optimization (QPSO) has been proposed by Wei [2], which introduced the concept of quantum, built a Delta potential well model to simulate the learning inclination of particles and designed a method of controlling the parameters on global level. As the benchmark functions shown, QPSO has better performance than PSO.

The origin and the development of mobile robot are also outline in Zhang's [3] paper. The mobile robot's prospect aspect in the future-intelligent robot has been presented. The path planning for mobile robot is the most important aspect of intelligent robot. The general conceptions, characteristic, classify based issue and some familiar methods of path planning are presented. In his paper, according to the characteristics of mobile robot path planning, Zhang [4] proposed a new method for mobile robot path planning is the Quantum-behaved Particle Swarm Optimization. Meanwhile, some invalid particles will be change into random valid particles once again. So expand your search range and keep part from get into local optimal.

Robert's [5] paper analyses the researching situation is elaborated and summarized of intelligent mobile robot. And then, he summarized the path planning of mobile robot and points out the development and research aspects of the path planning technology. And discusses the algorithm of path planning based on the D* algorithm (dynamic A* algorithm) and the partially-unknown environments. The D* algorithm is a kind of incompletion replanting, and makes use of the original planning information, in a way that combines the characters of the optimization and the real-time. D* algorithm is able to use the global planning and local information, also good at utilize the off-line planning and on-line planning. By researched on D* algorithm, an improved D* algorithm is studied in this thesis. In the view of process unknown obstacles, the experiment result shows that the improved D* algorithm can find a feasible path in an optimal time and which is effective and can result in higher quality path than the conventional D* algorithm at the same map environment. To consider the particularity of information partially-unknown environment, this thesis analyzes the performance and infections on sensors of robot system. The method of environment express is presented in Henten's paper [6]. And then, the research realized the localization and mapping of mobile robot and renews the map in time for mobile robot navigation, by using probability method which is based on Bayes estimate to fusion multi-sensor data from the environment.

II. THE FRAMEWORK OF THE PICKING UP BALL ROUTE PLANNING

Mobile robot technology involves multiple research areas and represents the frontier of high technology. Mobile robot technology has a wide range of applications in different walks of life. Mobile robot is capable of acquiring the information of environment and its own state to achieve the scheduled mission in the environment with obstacles. Navigation of mobile robot is the process of moving toward the target autonomously in the environment with obstacles. In the process of navigation, mobile robot has to carry out the accurate modeling of the environment, achieving the location of the pose and planning the optimal path from the starting point to the target point. Therefore, the research of environment modeling method, path planning algorithm and location method for mobile robot has theoretical and realistic significance.

Path planners differ as to how they effect this discrete decomposition. In any event, there are many similar characteristics which all path planners have:

Search Space: This represents the possible states, or positions, orientations and conditions of the robot, the world and its objects. A simple example is the x; y coordinates of a vehicle in the Euclidean space. More complex states may involve conditions as complicated as radio signal strength or fuel level.

Initial and Goal States: The plan is the way the robot will get from the initial to the goal state.

Criteria for Planning: The desired characteristics of the "best" plan, such as time, distance, or safety. These are yardsticks by which to optimize plans.

Constraints: Those items, which limit the range of plans that can be made, such as maintaining vehicle safety, stealth or the physical limitations of the robot.

Algorithm: This is the method by which the best plan is obtained given the criteria and constraints for planning.

Actions: A plan must also generate actions, or ways of moving from state to state.

Time: Planning always involves time in some way, even if not explicitly. A planner may include time in such ways as: "at time t the robot will be at point x, y", or "the path should take the least amount of time possible." Usually time is represented simply as a sequence of actions: "after Action A is completed the robot will do Action B".

Plan: The sequence of actions to move from the start configuration to the goal configuration.

There are a number of considerations for path planning that will influence the design of the system and criteria by which they are judged:

Environment: Does path planner sufficiently represent the environment? Is the application indoor or outdoor? Is it cluttered or relatively open?

Robot Structure: Does the path planner provide a sufficient but not excessively detailed representation of the vehicle with respect to size and mobility constraints?

Space and Time Complexity: Can it operate fast enough so the robot does not need to stop and think?

Dynamic or Unknown Worlds: Can the path planner deal with changing information or goals

Optimality: Requirements can be based on minimum distance traveled, time taken, vehicle safety, etc.

Completeness: Will it find a path if one exists?

The most of work in motion planning or path planning algorithms was divided in three general strategies for decomposition:

1. Cell decomposition: discriminate between free and occupied cells.

2. Road map: identify a set of routes within the free space.

3. Potential field: impose a mathematical function over the space.

Potential Fields have the flaw of containing local minima other than the goal in which the robot can be stuck. Much of the efforts of adapting potential fields have been at overcoming this flaw.

Potential fields are often referred to as a local method, as opposed to a global method, because the effect of the field on the robot is almost exclusively based on obstacles near it. Obstacles far away have little to no effect on the robot's motion, and so it can't be a useful planning method. There are simpler and more efficient ways to use the potential field for path planning.

PRMs are usually based on binary obstacles that most other roadmap planners use, rather than a gradual costing. This means that obstacles need to be well defined and generating variable path costs is more difficult than with other methods. When obstacles are added or removed from the map and the entire roadmap must be regenerated. Because generation of the roadmap is slow and cannot be done in real time, the planner functions poorly when the information is changing often or if the initial information is incorrect. Figure 1 shows a poorly covered and a well-covered PRM.

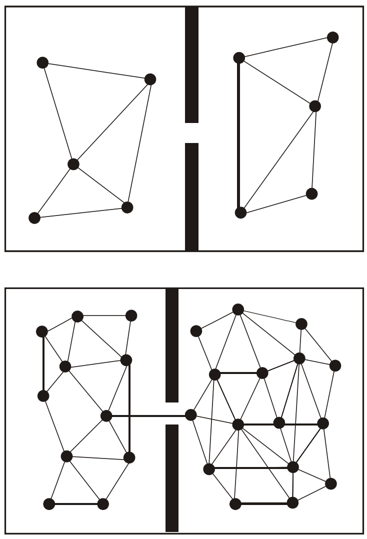

Figure 1. A poorly covered and a well-covered PRM

The path planning for mobile robots based on the proposed optimization algorithm includes two steps: The first step is to establish a free-space mobile robot model; the second step is adopting the quantum-behaved particle swarm optimization algorithm to find out the global optimal path. The computer simulation experiment was carried out, by comparing the results confirmed that the method proposed by this paper, both in convergence rate, or in a dynamic convergence characteristics than the particle swarm optimization, as well as other planning algorithm of mobile robot global path better planning methods. Finally, conclusions are given with recommendation for future work. Figure 2 shows the basic framework and model.

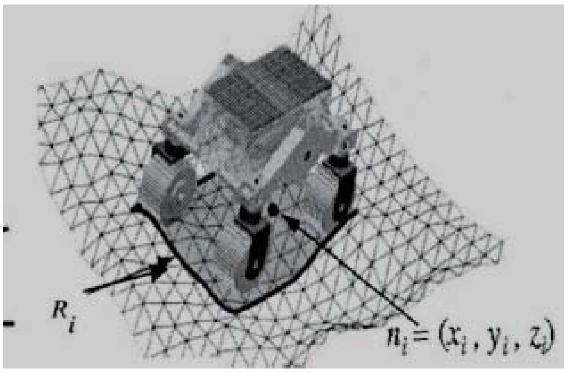

Figure 2. A basic model.

III. THE PICKING UP BALL ROUTE PLANNING ALGORITHM

It is necessary to develop automatic mapping algorithms for the construction of the ground model and to develop good algorithms for path planning, because good quality terrain models are becoming more and more important, as applications are being developed that demand better surface orientation information than is available from traditional interpolation techniques.

We noted that the 3-D terrain model is the digital representation of terrain surface in spatial position, and the modeling of 3-D terrain can be classified into four: based on scatter points, based on triangulation, based on the grid and mixed surface.

It is well know from linear algebra that any matrix A with M rows and N columns can be written in terms of its singular value decomposition, i.e., as the product of an M×M column-orthogonal matrix U, and an M×N diagonal matrix D, with nonnegative diagonal elements, and the transpose of an N×N orthogonal matrix V. That is,

A=UDVT, (1)

Here, D=(diag(σ1, σ2,…, σq), 0) or its transposition, which depends on M<N or M>N. And 0 refers to zero matrix. Moreover, σ1≥σ2≥…≥σq>0, and the numbers σq are called the singular values of A. If M=N, D is an M×M diagonal matrix with the singular values in decreasing order on its main diagonal. If M<N, D consists of a M×M diagonal matrix with the M singular values on its main diagonal (in decreasing order) extended on the right-hand side with a M×(N-M) matrix of zeros. If M>N, D consists of a N×N diagonal matrix with the N singular values on its main diagonal (in decreasing order) on top of a (M-N) ×N matrix of zeros. Let x(i) as sample data, here i=1,2,…, N. The matrix A is constructed by phase space reconstruction theory.

That is,

$$A=\begin{bmatrix} x_1 & x_2 & \cdots & x_n \\ x_2 & x_3 & \cdots & x_{n+1} \\ \vdots & \vdots & \vdots & \vdots \\ x_m & x_{m+1} & \cdots & x_{m+n-1} \end{bmatrix}, \quad (2)$$

Here, 1<n<N, and m+n-1=N, this matrix is called Hankel matrix.

It could be defined by singular value as follows:

$$E=\sum_{i=1}^{q}\sigma_i^2 \quad (3)$$

Then, define the energy difference spectrum of singular value and normalized it as follows:

$$p(i)=\frac{\sigma_i^2-\sigma_{i+1}^2}{E}, \quad (4)$$

$$f(x)=\sin(2\pi x f1/fs)+\sin(2\pi x f2/fs)+i(x) \quad (5)$$

ux=u is a constant and the formula should be as follows:

$$\frac{\partial C}{\partial t}=D_L\frac{\partial_2 C}{\partial x^2}-u\frac{\partial C}{\partial x} \quad (6)$$

$$\begin{aligned} &C(x,t)\,|_{t=0}=0 && 0\le x<+\infty \\ &C(x,t)\,|_{x=0}=C_0 && t>0 \\ &C(x,t)\,|_{x\to+\infty}=0 && t>0 \end{aligned} \quad (7)$$

After Laplace change, the standard normal distribution function is solved as follows:

$$C=1-\Phi_{0.1}\left[\frac{x-ut}{\sqrt{2D_L t}}\right] \quad (8)$$

Assume the relative concentrations 0.16 and 0.84 occur at the time of t0.16 and t0.84, then we can get:

$$D_L=\frac{1}{8}\left[\frac{x-ut_{0.16}}{\sqrt{t_{0.16}}}-\frac{x-ut_{0.84}}{\sqrt{t_{0.84}}}\right] \quad (9)$$

The following equation (10)-(11) is shown as:

$$I_T^2=U_T^2/R^2=4KT\Delta f/R \quad (10)$$

$$U_T=\sqrt{4KTR_1\Delta f_e} \quad (11)$$

The optimization problem that is solved in MPC regulator is described as X_t which can be represented by the K Gauss equation seen in (12)-(13).

$$P(X_t)=\sum w_{i,t}\times\eta(X_t,\mu_{i,t},\sum i,t) \quad (12)$$

$$\eta(X_t,\mu_{i,t},\sum i,t)=\frac{1}{(2\pi)^{\frac{n}{2}}\,|\sum i,t|^{\frac{1}{2}}} \quad (13)$$

$$e^{-\frac{1}{2}(Xt-\mu i,t)^T\sum_{i,t}^{-1}(Xt-\mu i,t)}$$

The combination of plant and disturbance models, in the case of the constant output disturbance, is defined as:

$$y\ (t) = y(t) - \phi^T(t)\theta \tag{14}$$

If we have unbiased prediction of the steady state and the optimization problem has a feasible solution, then we can conclude in equation (15)-(17):

$$w_{i,t} = (1-\alpha)\times w_{i,t-1} + \alpha \tag{15}$$

$$\mu_{i,t} = (1-\rho)\times \mu_{i,t-1} + \rho \times X_t \tag{16}$$

$$\sigma^2_{i,t} = (1-\rho)\times \sigma^2_{i,t-1} + \rho(X_t, \mu_{i,t-1})^T \times (X_t - \mu_{i,t-1}) \tag{17}$$

Consider delay, the L can be expressed as:

$$\mathcal{L}^0 = \begin{Vmatrix} C^0_{ijkl} & e^0_{kij} \\ e^{0T}_{ikl} & -\eta^0_{ik} \end{Vmatrix} \tag{18}$$

These functions can be expressed in the following form:

$$C(\mathrm{x}) = C^0 + C^1(\mathrm{x}) \quad , \quad e(\mathrm{x}) = e^0 + e^1(\mathrm{x}) \quad , \eta(\mathrm{x}) = \eta^0 + \eta^1(\mathrm{x}) \quad , \rho(\mathrm{x}) = \rho_0 + \rho_1(\mathrm{x}) \tag{19}$$

The value with superscript of 1 represents the difference below:

$$C^1 = C - C^0 \,, e^1 = e - e^0 \,, \eta^1 = \eta - \eta^0 \,, \rho_1 = \rho - \rho_0 \tag{20}$$

The whole function can be simplified into the following integral equation set:

$$f(x,\omega) = f^0(x,\omega) + \int_V \mathcal{S}(x-x')(\mathrm{L}^1 F(\mathrm{y}') + \rho_1\omega^2 \mathbf{g}(R)\mathrm{T}_1 f(\mathrm{y}')]S(\mathrm{y}')\mathrm{dy}' \tag{21}$$

$f(t)$ is defined as:

$$[\frac{\partial}{\partial t} + \varepsilon]^2 f(t) = \delta(t) \tag{22}$$

$$\overline{g}(k,t) = \frac{1}{2\pi}\int_{-\infty}^{+\infty} \frac{e^{-i\omega t} d\omega}{k^2 + (\varepsilon - i\frac{\omega}{c})^2} = c^2\Theta(t)\frac{\sin(ckt)}{ck}e^{-\varepsilon t} \tag{23}$$

The next figure demonstrate an example of the navigation steps process of proposed algorithm applied from start point a to goal point d. In the graph, the graph has four nodes. Figure 3 shows the process of the algorithm.

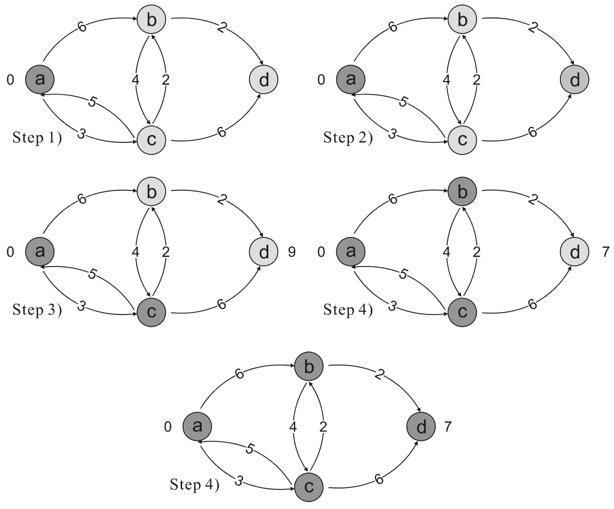

Figure 3. The step by step process of the algorithm.

IV. RESULTS AND DISCUSSION

In this part, we show the influence of the ground modeling in distance traversed and path developed for the mobile robot using the proposed method. Figure 4 shows the distances traversed for different value of weighting factor

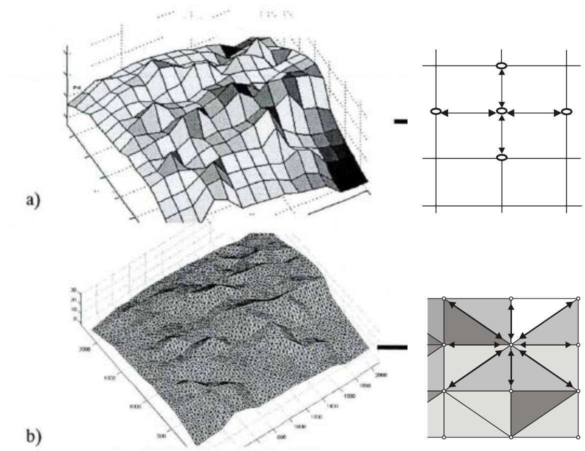

Figure 4. Distances Traversed for Different Value of Weighting Factor

In figure 4 a): traditional grid map every vertex has 4 edge neighbors and 4 vertexes neighbors. The traditional grid map provides four moving direction choices for each location.

In figure 4 b): triangular mesh map we can see that every triangle has 3 edge neighbors and 9 vertex neighbors, so it has 12 cell neighbors in a non-boundary triangle cell.

The triangle mesh map provides 12 moving direction choices for each location, and we know that the triangle one has good precision, high efficiency and facility of dealing with geo-character, such as rupture line, construction line which results in a much smoother path compared with the traditional grid map. This series of figures and table we show deferent path developed with different cost functions in different terrain models to see the influence of smoothing process basing in triangular B-spline method.

V. CONCLUSION

In this paper, the author researches on the picking up ball route planning algorithm for ball picking robot to obtain maximum efficiency. For global path planning of mobile robot, simplified visibility graph suitable for path planning algorithm of mobile robot is proposed to solve the problem of environment modeling. Navigation of mobile robot is the process of moving toward the target autonomously in the environment with obstacles. In the process of navigation, mobile robot has to carry out the accurate modeling of the environment, achieving the location of the pose and planning the optimal path from the starting point to the target point. The computer simulation experiment was carried out, by comparing the results confirmed that the method proposed by this paper, both in convergence rate, or in a dynamic convergence characteristics than the particle swarm optimization, as well as other planning algorithm of mobile robot global path better planning methods. Therefore, the research of environment modeling method, path planning algorithm and location method for mobile robot has theoretical and realistic significance. The representation of environment model is simplified. The purpose of reducing the number of alternative paths in the process of path planning is achieved, which improves the efficiency of the follow-up path planning algorithm.

ACKNOWLEDGMENT

This work is supported by the Academician workstation project from Shaanxi University of Technology (fckt201511).

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