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Mobile Robot Path Planning in Three-Dimensional Environment Based on ACO-PSO Hybrid Algorithm*

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***Abstract* - A ACO-PSO hybrid algorithm is proposed in order to solve mobile robots path planning problem in three-dimensional environment. In this study, firstly, proposed a simple regulation for obstacles compartmentation in three-dimensional (3-D) environment, through which non-configurable terrain could be transformed into configurable terrain; established the environment model through Bitmap method based on the regulation, and divided 3-D movement domain for robots into transitable domain and impedient domain. Secondly, planed the paths of mobile robots through swarm intelligence algorithm. Ant colony optimization (ACO) was used to plan paths in robots transitable territory; particle swarm optimization (PSO) was applied to optimize the parameters of ACO, thus through ACO-PSO hybrid algorithm to deal with path planning problem. At last, carried on simulation experiments under two kinds of 3-D terrain; the results show that the method is efficient and feasible.**

Index Terms – mobile robots; path planning; ant colony optimization (ACO); particle swarm optimization (PSO); hybrid algorithm

I. Introduction

The mobile robots path planning problem means a proper moving path for the robot from a designated start point to a designated goal point in a workplace with obstacles.

Existing algorithms on the path planning problem is proceeding from planning in two-dimensional environment [1-3], some of which purportedly can be extended to path planning in three-dimensional environment. In fact, because of the unique space-time complexity of path planning in 3-D environment, the planning algorithms in 2-D environment can not be generalized derectly. In order to deal with mobile robots path planning problem in three-dimensional environment, Vasuderan [4] used case-based reasoning algorithm, which adjusts path through local obstacles, but sometimes can not be optimal; K.P.Caroll [5] proposed A* searching algorithm, which can apply in high-dimensional planning problems, but with increasing dimensions, it is difficult to meet the space-time requirements of planning problem; W.Warren [6] used artificial potentials method, which will inevitably be local optimal, and when applied to some complex optimization criterias, artificial potentials method can not be promoted directly; X.B.Hu [7] established the space environment model, then planed the 3-D routes for aircrafts through ant colony algorithm. But relative to aircrafts, the movement of mobile robots is a kind of movement with restriction on free-degree, so that we can not detectly apply the method Reference [7] proposed. From the analyse above, we can see that it is important to set up a specialized solution for mobile robots path planning problem in 3-D environment.

There are two core steps about path planning methods: environment modeling and planning algorithm. In this paper, firstly proceeding from the reality, proposed a simple regulation for obstacles compartmentation in three-dimensional(3-D) environment. Through that regulation, established environment model based on Bitmap method. Thus transformed 3-D non-configurable terrain into configurable terrain. Secondly planed paths for robots: ACO [8] was used to plan paths for robots in deep-sea transitable territory; PSO [9] was applied to optimize the important parameters of ACO. Thus the important parameters , of ACO can be select self-adapted through PSO in according with different terrains. Finally carried on simulation experiments, and the results validates the feasibility of the method.

II. Environment modeling

Path planning problem in 2-D environment almost established environment model through 2-value fuction. Environment model was divided into strict transitable domain and impedient domain; transitable domain was regarded as segments of 2-D plane. Obviously, these algorithms can not be fully applied to the actual planning problems in 3-D environment. When the mobile robot has certain climbing ability and territory slope is small, mobile robots can climb, and do not need to steer clear of obstacles. The 3-D domain where mobile robots can climb can be look on as common transitable domain. Therefore, S.L.Laubach [10] pointed out the key of future path planning is the terrain traver-sability.

A. Obstacles Compartmentation

About obstacles compartmentation, H.Seraji [11] carried on fuzzy classifying with some information such as terrain slope, terrain softness, roughness and so on; D.B.Gennery [12] calculated terrain altitude and slope through smooth interpolation; A.Shirkhodaie [13] designed fuzzy classifier, regulation classifier and neural network classifier to distinguish terrain types; S.Singh [14] scale terrain characters through correlative parameters: roll, pitch and roughness. The above methods increase the complexity of environment modeling, and the planning algorithms based on above

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menthods have no good real-time property. Aiming at this problem, proposed a simple regulation for obstacles compartmentation in 3-D environment based on terrain slope. In the first, some restrictions must be added to planning problem: assume that the ground of movement domain for mobile robots is hard substrate, where mobile robots will not subside; the surface are one-rank humdrum and vertical consecutive. In this paper, based on climbing grade ability of robots, environment was divided into transitable territory and impedient territory according to terrain slope. The method is simple, and algorithm is real-time. Territory slope is the angle between territory surface tangent plane and normal plane at a certain positional point, the value of which equal to the angle between tangent and normal at that point. Such as Fig.1.

Territory slope θ_p is represented as the average gray of 8 neighbors at the certain positional point p. As shown in Fig.1, p_i (i=1,2,⋯8) has exclusive coordinate $p_i(x_i,y_i,z_i)$ in earth reference frame *O-XYZ*.

$$\theta_p = \arctan\left(\frac{1}{8}\sum_{i=1}^{8}\left|\frac{z_i - z}{\sqrt{(x_i - x)^2 + (y_i - y)^2}}\right|\right) \qquad (1)$$

In this study, mobile robots are tracklayers, considering the climb ability of tracklayers. If at certain positional point p, $_p$ 30°, p will be look as a impedient point. The set of impedient point becomes impedient domain.

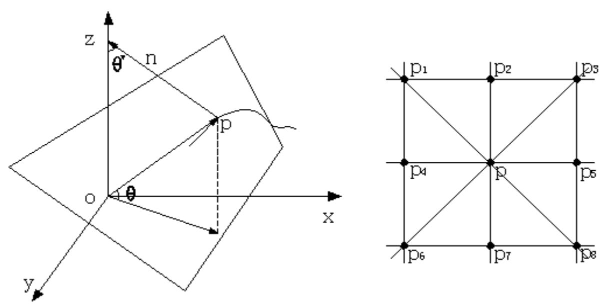

Fig. 1 The sketch map of terrain gradient

B. Modeling Method

For mobile robots path planning problem in 3-D complex environment, the global information usually is unknown. That means it is very needed to detect real-time environment information surrounding through bodywork detecting system.

Assume that robots can detect environment information of $M*N$ rectangular area in front($M>R$, $N>R$,R is the diameter of robots). $M*N$ rectangular area is denoted by dynamic window for path planning. With robots' moving and detecting, the environment information in dynamic window continuously updates dynamically, and robots can real-time plan the current path. Arbitrary positional point p in dynamic window, has unique coordinate $p(x,y,z)$ correspondingly. The reference frame of dynamic window is earth reference frame *O-XYZ,* and the reference frame of environment information real-time detected by robots is bodywork reference frame *O'-X'Y'Z'*. That means it is needed reference frame transforming. The DEM in bodywork reference frame *O'-X'Y'Z'* must be transformed into DEM in earth reference frame *O-XYZ.* Such as Fig. 2 shows:

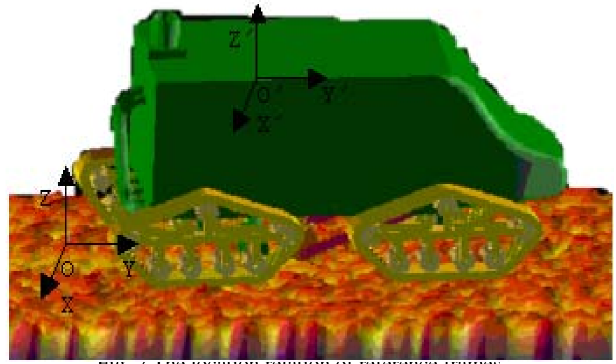

Fig. 2 The location relation of reference frames

Assume that the coordinate of random positional point in earth reference frames *O-XYZ* under deep-sea environment is $u=[x,y,z]^T$; the origin coordinate of *O'-X'Y'Z'* in *O-XYZ* is $u^{\circ}=[x^{\circ},y^{\circ},z^{\circ}]^T$; the coordinate of that positional point in bodywork reference frame *O'-X'Y'Z'* is $u'=[x',y',z']^T$, the transform formulae are:

$$u=u^{\circ}+Tu' \qquad (2)$$

$$T=\begin{bmatrix} \cos\alpha\cos\gamma & \cos\beta\sin(\gamma-\delta) & -\cos\alpha\sin\beta\sin\gamma-\cos\beta\sin\alpha\cos(\gamma-\delta) \\ \cos\alpha\sin\gamma & \cos\beta\cos(\gamma-\delta) & -\sin\alpha\cos\beta\sin(\gamma-\delta)+\cos\alpha\sin\beta\cos\gamma \\ \sin\alpha & -\sin\beta & \cos\alpha\cos\beta\cos\gamma\cos(\gamma-\delta)+\cos\alpha\cos\beta\sin\gamma\sin(\gamma-\delta) \end{bmatrix} \qquad (3)$$

In these formulae: T is poise space matrix, which represents the space poise of mining robots; α is pitch angle; β is roll orientation angle; γ is navigational angle; $\delta=\arcsin(\tan\alpha\tan\beta)$.

In this way, mobile robots can detect real-time environment information, which will be transformed into DEM data in dynamic window. In $M*N$ dynamic window, robot located at the under upright center.

Based on Bitmap method, dispersing the 3-D map in earth reference frame *O-XYZ* into pixels; connecting boundaries of the region where the territory slope exceed 30º and composing close impedient region separately; expanding the boundaries of impedient regions along normal direction to width R_f, and

$$R_f=R+R_s \qquad (4)$$

where R is the diameter of robots; R_s is the safety width for robots' swerving and evading collisions.

The expanded regions make up of impedient territory. In robot 3-D environment model, transitable territory is the surplus set of impedient territory. After environment modeling, robot movement can be look as particle movement in transitable territory.

The space R_h between two sequential pixels is

$$R_h=eR_f \qquad (5)$$

where e (0,1). If the value of R_h is too large, planning is not precise enough; If the value of R_h is too small, the computing amount is enlarged, and the algorithm has no good real-time property.

Definition 1 Assume that p_i is a certain pixel in environment model, $\forall p_i$, has definite coordinate $p_i(x_i,y_i,z_i)$; P is the set of pixels; O is the set of pixels covered by expanded obstacles; $W=O^c$ is the transitable pixels for robots, obviously $O \cup W=P$; p is the set of 8 neighbours of random pixel p.

Definition 2 The line segment between two pixels p_i 、p_j $P(i,j \quad N_+, i \neq j)$ is denoted one esge L_{ij}，and the length of L_{ij} is denoted $d(p_i,p_j)$, which is defined as

$$d(p_i,p_j)=\sqrt{(x_i-x_j)^2+(y_i-y_j)^2+(z_i-z_j)^2} \tag{6}$$

Therefore, the length d_{Nc} of the shortest path L_{Nc} in NO. $Nc(Nc \quad N_+$, and $Nc \quad Ncmax)$ iteration is defined as

$$d_{Nc}=\sum_{j=1}^{n} d(p_{j-1}-p_j) \tag{7}$$

where n is the tatal number of steps in NO. Nc iteration; $Ncmax$ is the largest number of iterations. In each dynamic window, the intent of planning is to find a points set $Q=\{S,p_1,p_2,\cdots,p_{n-1},G\}$ from start point S to goal point G. Set $S=p_0$, $G=p_n$, $\forall p_i(i=0,1,\cdots,n)$, $p_{i+1} \quad p_i$, $p_{i+1} \notin p_j(j=0,1,\ \cdots,i)$, and $p_i \notin O$.

III. Planning Algorithm

ACO and PSO, as two kinds of swarm intelligence algorithm are two hot points recently, and have been widely applied in lots of optimal problems. In this paper firstly ACO was used to plan paths for robots in deep-sea transitable territory; then PSO was applied to optimize the important parameters , of ACO.

A. *The Solution Process by ACO*

There are three core steps of ACO: walk regulations, local updating and overall updating. Focus on these three steps, material algorithm is described as follows:

1) Walk Regulations: After initializing, each ant seek next transitable pixel by the following regulations, then walked between the two positional points:

$$p_j=\begin{cases}\arg\max[\tau_{ij}^{\alpha}(t)\eta_j^{\beta}(t)] & if\,(q \le q_0)\\ X & else\end{cases} \tag{8}$$

$$p_{ij}^{k}(t)=\frac{\tau_{ij}^{\alpha}(t)\eta_j^{\beta}(t)}{\sum_{r\in F}\tau_{ir}^{\alpha}(t)\eta_r^{\beta}(t)} \tag{9}$$

$F \quad \Theta p_i$, $F \notin O$ and $F \notin tabu_k$

Where:

$$\eta_j(t)=\frac{E}{d(p_j,G)} \tag{10}$$

In the above formulae, X is a stochastic variable, which correspond with a certain pixel; q is a stochastic numeral from 0 to 1; q_0 is a critical value set through initialization; $\tau_{ij}(t)$ is the surplus pheromone on edge L_{ij} at t instant; $\eta_j(t)$ is a heuristic function rested with formula (9); E, α, β respectively is positive constant; $p_{ij}^{k}(t)$ represents the probability for ant $k(k \in N_+$,and $k \leqslant m$, m is the total number of ants)moving from p_i to p_j at t instant ; $tabu_k$ is the set of pixels ant k had passed.

2) Local Updating: After each ant had passed an edge, updating pheromone on each edge according to formula (11).

$$\tau_{ij}(t+1)=(1-\rho_1)\tau_{ij}(t)+\rho_1\Delta\tau_{ij}^{k} \tag{11}$$

$$\Delta\tau_{ij}^{k}=\begin{cases}\dfrac{Q_1}{\sum^{u} d_e} & if: ant\ k\ passed\ L_{ij}\\ 0 & else\end{cases} \tag{12}$$

In the formula above, Q_1 is a constant; $_1$ is local pheromone volatilization coefficient; d_e is the length of edge ant k has passed ; u is the number of edges which ant k has passed in same iteration; When $_{ij}(t+1)<{}_{min}$, set $_{ij}(t+1)={}_{min}$ ($_{min}$ is a constant).

Ant group proceeded to search next pixel, when ant k found planing aim point $G=p_j$, a integrity path L_k was gained. The length of the integrity path d_k was calculated through formula (7) and memorized. When each ant reached G, each integrity path found by each ant was compared. Length of the shortest path L_{Nc} was memorized, which was named d_{Nc}.

3) Global Updating: When a iteration finished, the pheromone on L_{Nc} needed to update in speeding up the convergence:

$$\tau_{ij}^{Nc+1}=(1-\rho_2)\tau_{ij}^{Nc}+\rho_2\Delta\tau_{ij}^{Nc} \tag{13}$$

$$\Delta\tau_{ij}^{Nc}=\begin{cases}\dfrac{Q_2}{d_{Nc}} & if: L_{ij}\ belongs\ to\ L_{Nc}\\ 0 & else\end{cases} \tag{14}$$

In the formula above, Q_2 is a constant; $_2$ is global pheromone volatilization coefficient; τ_{ij}^{Nc} is the pheromone amount on L_{ij} after NO. Nc iteration finished.

After a iteration finished, added 1 to Nc till the max iteration number. The best path length of each iteration should be compared each others, then memorized and exported the shortest path L_{min}.

B. *Parameters Ttraining by PSO*

From the depiction above we can see that , are important parameters of ACO. In this paper, , can be self-adaptive selected through particle swarm search, that change the usual pattern of selecting through experience, and improve accuracy of the algorithm.

PSO simulates the "searching food" behavior of bird swarm, and carring on searching by using v-x(velocity-location) model. In training , by PSO, assume that there are h particles in particle swarm, and each particle is l-dimensional. A solution to choose is called a particle, whose preponderant degree is decided by fitness function. Each particle has a velocity vector, namely a speed with value and orientation. In each iteration process, other particles in swarm keep searching in solution space by following optimal particle. Particles update their velocity and location through individual optimal solution p_B and swarm optimal solution $g_{B.}$ Operating the particles by the following formulas:

$$v_{e,f}^{t+1} = \omega v_{e,f}^{t} + \frac{1}{\Delta t} c_1 r_1 (p_{e,f}^{t} - x_{e,f}^{t}) + \frac{1}{\Delta t} c_2 r_2 (p_{g,f}^{t} - x_{e,f}^{t}) \tag{15}$$

$$x_{e,f}^{t+1} = x_{e,f}^{t} + \Delta t v_{e,f}^{t+1} \tag{16}$$

Where, $v_{e,f}^{t}$, $x_{e,f}^{t}$ separately is the velocity and location of NO. f(f N_+, and f l) dimensional component of NO. e(e N_+, and e h) particle; $p_{e,f}^{t}$, $p_{g,f}^{t}$ separately is the optimal location of NO. e(e N_+, and e h) particle and swarm NO. f(f N_+, and f l) dimensional component at t instant; t is unit time; r_1 and r_2 are random number between 0 and 1; c_1 and c_2 separately is acceleration weight of NO. e particle attracted by p_B and g_B; is the inertia weight, and is non-negative. linearly varies from 0.9 to 0.4, that can slow down the movement of the particles. Iteration termination condition is reaching the largest iteration number 20 or the optimal location can meet predetermined minimum value of adaptation threshold.

C. *Algorithm Steps*

Step1: Initialization: The start point S is added to $tabu_k$(k=1,2,⋯,m), and m ants are placed on S; With setting $_{ij}$(0)= $_0$ ($_0$ is a constant), 0 is set to the iteration counter NC for seeking food; the iteration maximum is $Ncmax$.

Step2: Ant moving: Each ant in ant group move a step according to formulae(8-10) based on walk regulation.

Step3: Local updating: After each ant has moved a step, update local pheromone on each edge according to formula (11).

Step4: Iteration process: Ant group proceeded to search next pixel. when ant k found aim point G, a integrity path L_k was gained. The length of L_k was calculated according to formula(7). When each ant reached G, each integrity path found by each ant was compared. The length of the shortest path L_l was noted down, whose lentgh is d_1.

Step5: Global updating: When each ant arrived at G, update global pheromone on each edge according to formula (13).

Step6: Iteration complete: After a iteration finished, 1 was added to Nc till the max iteration number. The best path length of each iteration should be compared each others, then noted down and exported the shortest path L_{min} among them.

Step7: Parameter optimizing: PSO was used to optimize important parameters , of ACO. Repeating **Step1- Step6.**

Step8: Results exporting: Found the optimal combination of , ,and exported. Exported the optimal results.

IV. Simulation Experiments

Based on the above analysis, mathematical simulation software MATLAB was used to carry on experiment simulation study on PC. The hardware scheme of PC is 256M EMS memory、Pentium Ⅳ 2.6G. Setting m=10，$Ncmax$=40， $_1$=0.65， $_2$=0.55，Q_1=2，Q_2=4, c_1=1.9, c_2=2.0.

In simulation experiments, carried out path planning in two kinds of 3-D terrain separately. The two series of combinations of and show in TABLE I and TABLE II The two simulation result figures show in Fig. 3 and Fig. 4.

TABLE I
THE COMBINATIONS OF AND FOR TERRAIN 1

			The length of optimal path	Run time
1	5.047	2.372	671.3	10.73
2	6.014	3.713	672.6	10.97
3	3.438	4.561	672.9	11.24
4	2.757	5.634	673.3	10.82
5	4.381	2.296	674.1	11.68
6	1.952	5.053	674.7	12.77

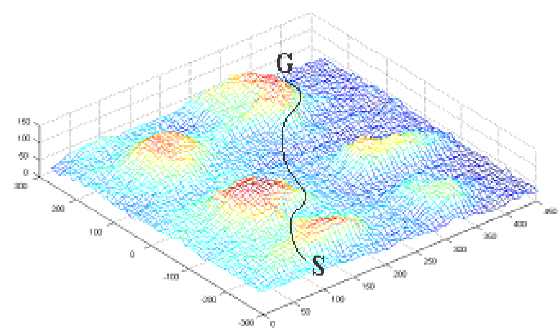

Fig. 3 The simulation result 1

TABLE II
THE COMBINATIONS OF AND FOR TERRAIN 2

			The length of optimal path	Run time
1	2.234	2.396	357.1	16.24
2	2.965	3.147	358.9	16.72
3	4.687	3.174	359.2	16.93
4	5.823	4.467	359.8	17.18
5	6.188	5.213	360.3	17.56
6	3.569	4.742	361.7	16.33

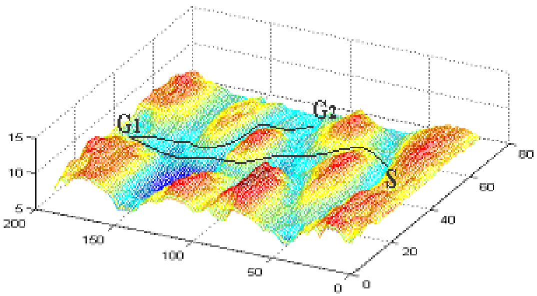

Fig. 4 The simulation result 2

In Fig.5, G_1 and G_2 are two planning aim points. At the same time, G_1 is also the planning start point for G_2. The path lentgh in Tab. 2 is sum of two planning.

From the results above we can see that in terain 1 shows in Fig. 1, when =5.047, =2.372, the planning tesults are optimal; in terain 2 shows in Fig. 2, when =2.234, =2.396, the planning tesults are optimal. For distinct terrain the optimal combination of and is determinate. Simulation results indicate that the method used in this study can reach satisfying precision under the price of a certain period of time.

V. Conclusion

Path planning problems for mobile robots in 3-D environment medal is one of the important issues, that need robots real-time plan their mining paths without global information. This paper starts from a simple regulation for obstacles compartmentation in 3-D environment. Furthermore, through that regulation, 3-D environment model of path planning problems for mobile robots is set up based on Bitmap method. So that robots can plan their mining paths through swam intelligence algorithm. With ACO and PSO, the path planning can carry out in different terrains. The simulation results show that the method is efficient and feasible. At the same time, this paper can provide a valuable reference for mobile robots path planning in complex environment.

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