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Ant Colony Algorithm for FFSR Collision Avoidance Motion Planning

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Abstract: Aiming at seeking optimal motion paths for Free-flying Space Robot (FFSR) in the obstacle environment, Ant Colony Algorithm (ACA) for obstacle avoidance motion planning has been proposed. Firstly, FFSR kinematics and motion path model has been established on the basis of linear momentum and angular momentum conservation laws followed by FFSR in a space microgravity environment. Secondly, ACA for FFSR collision has been proposed and a key research has been made on how to determine objective function, how to select path configurations and how to update pheromones and algorithm and realize the critical steps. Finally, the correctness and effectiveness of the algorithm proposed has been verified via computer simulation. The research results indicate that ACA based on swarm intelligence provides a new motion planning strategy and idea for FFSR collision avoidance motion planning and has good application prospect.

Key words: Motion planning, ant colony algorithm, free-flying space robot, collision avoidance

INTRODUCTION

With the great progress of human's exploration on moon, intelligent robot will play an increasingly decisive role in development and application of space and moon resources in the future. Free-flying Space Robot (FFSR) is a new intelligent robot consisting of satellite body and mechanical arm (Fig. 1). Since FFSR's satellite body carries a gas thruster, it can fly freely or floats in a space microgravity environment which extends the work space of FFSR. Therefore, FFSR can replace astronauts to engage in various operations in and out of the cabin and it will certainly be one of the main research directions for spatial intelligent robots. However, FFSR can carry limited fuels, so it will be of great significance to research its collision avoidance motion planning in order to improve FFSR's work efficiency and prolong its service life in orbit (Aghili, 2009; Abiko and Hirzinger, 2008).

At present, the scholars of various countries have done lots of researches on robot motion planning. The representative achievements include traditional optimization method, artificial potential field method (Bennet and McInnes, 2010), neural network method (Deng *et al*., 2010) and genetic algorithm (Xing *et al*., 2007). The traditional optimization method lacks sufficient robustness in the complex nonlinear optimization for robot motion planning. The artificial potential field method can facilitate the real-time control for bottom layer but lacks overall information and is problematic in local optimum. The neural network method has a good learning ability but the network structure is huge and the threshold values of neurons will change as the time changes when there are many obstacles and dynamic environment. The genetic algorithm has good overall searching ability but the environment model has to be established when the environment changes and the search space is huge.

Ant Colony Algorithm (ACA) is a bionic intelligent optimization algorithm which was firstly proposed by Italian scholars M. Dorigo, *et al*. The operating principle of this algorithm is a positive feedback mechanism or is called reinforcement learning system. It is a reinforcement learning algorithm based on Monte Carlo method (Dorigo and Di Caro, 1999; Dorigo and Stutzle, 2004; Afshar, 2010). The final convergence on optimal paths can be achieved by updating pheromone. Integrating human intelligence, it is applicable for concurrent computation and multi-objective optimization. As a distributed, overall and universal random optimization method, it has been successfully applied in Traveling Salesman Problem (TSP), assignment problem, job-shop problem and robot motion planning etc. A number of good experimental results have been obtained (Guo *et al*., 2007; Zhu and Zhang, 2005; Mao *et al*., 2006).

Optimal strategy for motion paths based ACA is described in this study. ACA is properly improved to be applicable for FFSR collision avoidance planning. An optimized motion path is found by calculating the shortest path between critical configuration points and start and goal configuration points and through the cooperative work of ant colony.

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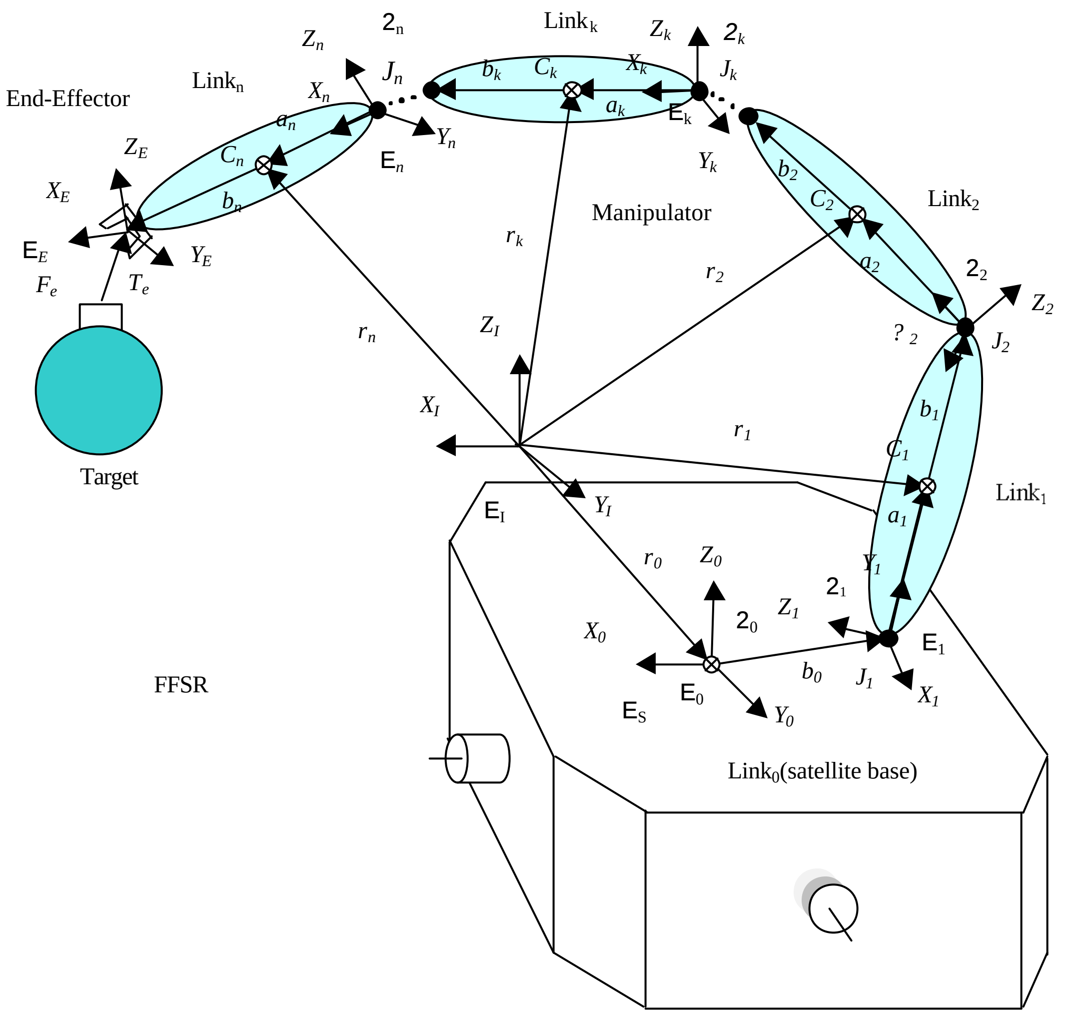

Fig. 1 Free-flying space robot kinematic model

BUILDING OF FFSR MOTION PATHS

Since FFSR is of nonholonomic redundancy, the motion of mechanical arm will interfere with the position and posture of satellite body. Its posture vector can be expressed as:

$$q = \left[x_c, y_c, z_c, \alpha_s, \beta_s, \gamma_s, \theta_1, \cdots, \theta_{n_d}\right]^T \in R^{n_d+6}$$

(n_d represents the number of degrees of freedom for FFSR's mechanical arm; $[x_c, y_c, z_c] \in R^3$ and $\Theta = [\alpha_S, \beta_S, \gamma_S] \in R^3$ are position vector of mass center of satellite body and posture vector respectively:

$$\theta_M = \left[\theta_1, \cdots, \theta_{n_d}\right]^T \in R^{n_d}$$

is joint angle vector of mechanical arm. When making the movement in a microgravity environment, FFSR system follows linear momentum and angular momentum conservation laws. According to these two laws and through a series of inference, FFSR kinematic equation can be obtained in Eq. 1 (Umetani and Yoshida, 1989; Li *et al*., 2008; Li, 2009):

$$\dot{\Theta} = G(T, ?_M)\dot{\theta}_M \qquad (1)$$

To ensure safety and universality, suppose the obstacle is expressed as a spherical set $C_{obs} = \{(p_{obs_i}, r_{obs_i}) \mid i = 1, 2, \cdots, N_{obs}\}$ wherein, p_{obs}, r_{obsi} represent position vector of sphere center and radius of No. i obstacle respectively.

Set start configuration of FFSR as q_s and goal configuration as q_g. There are some obstacles C_{obs} between q_s and q_g. FFSR collision avoidance motion planning is described as: seeking a short and safe path from start configuration q_s to goal configuration q_g.

To facilitate the solution, Cartesian coordinate system is changed. Define the direction connecting FFSR from start configuration q_s to goal configuration q_g as z' axis and change mass center of FFSR's satellite body as the origin of coordinates in a new coordinate system Σ_B(O'-x'y'z'). Then, the change relation between the coordinate system Σ_B and inertial coordinate system Σ_I(o-xyz) is shown in Eq. 2:

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} c_\alpha c_\beta & c_\alpha s_\beta s_\gamma - s_\alpha c_\gamma & c_\alpha s_\beta c_\gamma + s_\alpha s_\gamma \\ s_\alpha s_\beta & s_\alpha s_\beta s_\gamma + c_\alpha c_\gamma & s_\alpha s_\beta c_\gamma - c_\alpha s_\gamma \\ -s_\beta & c_\beta s_\gamma & c_\beta c_\gamma \end{bmatrix} \begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = R(\alpha_s, \beta_s, \gamma_s) \begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} \quad (2)$$

wherein, $c_* \equiv \cos(*)$, $s_* \equiv \sin(*)$, represents α_S, β_S or γ_S. The position vector of sphere center of the obstacle in the inertial coordinate system Σ_I is $p_{obs_i} = [x_{obs_i}, y_{obs_i}, z_{obs_i}]^T$ and its general expression in the new coordinate system Σ_B is Eq. (3):

$$[x_{obs_i}, y_{obs_i}, z_{obs_i}]^T = R(\alpha_s, \beta_s, \gamma_s) * [x'_{obs_i}, y'_{obs_i}, z'_{obs_i}]^T + [x_c, y_c, z_c]^T \quad (3)$$

Divide the segment L_{SG} connecting FFSR's start configuration q_S and goal configuration q_G in the coordinate system Σ_B(o'-x'y'z') into m equal parts. The length of each equal part is shown in Eq. 4:

$$\Delta d = \sqrt{\sum_{i=1}^{n_d+6} \|q_g - q_s\|^2} / m \quad (4)$$

Make a vertical plane for L_{SG} at each equal diversion point, obtain L_1, L_2,..., L_{m-1} along x' direction, equally divide each segment L_i into $2n_{ac}$ parts, then ($2n_{ac}+1$) points will be obtained on each segment L_i. In the obstacle avoidance area, there will be $(m-1)\times(2n_{ac}+1)$ motion configuration points. That is $L_1(x'_1, y'_1, z'_1)$, $L_1(x'_1, y'_1, z'_2)$,..., $L_1(x'_1, y'_1, z'_2)$,..., $L_{m-1}(x'_{m-1}, y'_{m-1}, z'_{m-1})$... $L_{m-1}(x'_{m-1}, y'_{m-1}, z'_{m-2})$...$L_{m-1}$...$(x'_{m-1}, y'_{m-1}, z'_{2n+1})$, wherein, $L_1(x'_1, y'_1, z'_1)$ represents No. j point on No. i segment L_i. The path from start configuration q_s to goal configuration q_g can be expressed as Eq. 5:

$$(k_i = 1, 2, ..., 2n_{ac}+1) \text{Path} = \{q_S, L_1(x'_1, y'_1, z'_{k1}), L_2(x'_2, y'_2, z'_{k2}), ..., L_i(x'_i, y'_i, y'_{k_i})...L_{m-1}(x'_{m-1}, y'_{m-1}, y'_{k(m-1)}) q_G\} \quad (5)$$

The distance from the configuration point c_p (x'_i, y'_i, z'_g) on the segment L_i to the configuration c_q $(x'_{i+1}, y'_{i+1}, x'_j)$ on the segment L_{i+1} is expressed by:

$$d_{pq} = \sqrt{(\Delta d)^2 + \sum_{i=1}^{n_d+6} \|q_p - q_q\|^2} j, \; g = 1, 2, ..., 2n_{ac}+1$$

If the segment pq is intersected or tangent with the obstacle, then set its distance as infinite 8. The path length of No. k ant is shown in Eq. 6:

$$L_k = \sqrt{(\Delta d)^2 + (z'_{k_1})^2} + \sum_{k_i}^{m-2} \sqrt{(\Delta d)^2 + (z'_{k_{(i+1)}} - z'_{k_{(i)}})^2} + \sqrt{(\Delta d)^2 + (z'_{k_{(m-1)}})^2} \quad (6)$$

ACA FOR FFSR COLLISION

To save the valuable fuels for FFSR, the goal for FFSR motion planning in this study is set as: The paths that FFSR runs need to be the shortest one. Moreover, FFSR does not have to run through all configuration points but only needs to start from the start configuration point q_S and reach the goal configuration point q_G.

FFSR updates pheromones according to the objective function. The objective function does not only include the path length that the ant passes through but also include safety information for obstacle avoidance. In FFSR path planning, memory is not required in FFSR but only the nodes are selected from the next segment.

DETERMINATION OF OBJECTIVE FUNCTION

Suppose there are N_{obs} obstacles, the position vector of sphere center of each obstacle is $[x'_{obs_j}, y'_{obs_j}, z'_{obs_j}]^T$ and its radius is r_{obs_j}. The distance from the node (x'_i, y'_i, z'_{ki}) on the segment L_i to the obstacle can be shown in Eq. 7:

$$d_j = \sqrt{(x'_i - x'_{obs_j})^2 + (y'_i - y'_{obs_j})^2 + (z'_{k_i} - z'_{obs_j})^2} - r_{obs_j} \quad (7)$$

Since the pheromones in ACA are updated according to the objective function, specific issues need to be taken into consideration during the selection of objective function. That is, the path should be the shortest and can safely avoid the obstacles. From these two points, the objective function can be determined by taking the path length that the ant passes through and the distance from the selected discrete point on the path to the nearest obstacle. Its computational equation is shown in Eq. 8:

$$F_k = L_k + \delta \sum_{i=1}^{m-1} (1/d_{imin}) \quad (8)$$

wherein, L_k represents the path length that No. k ant passes through, d_{imin} represents the distance from configuration node i to the nearest obstacle and δ is obstacle avoidance coefficient. As δ is greater, the safety coefficient of FFSR will be higher. The distance from the selected node (x'_i, y'_i, z'_i) to the nearest obstacle is calculated by Eq. 9:

$$d_{imin} = \min\{d_1, d_2, \cdots d_j, \cdots, d_{N_{obs}}\} \quad (9)$$

SELECTION OF MOTION PATH CONFIGURATION

Suppose the time for the ants walking from the configuration point p on the segment L_i to any of configuration point's q on the next segment L_{i+1} is the same and it has nothing to do with the distance. Then all the ants will reach the goal configuration point and finish a cycle at the same time. If the ant colony moves to the segment L_i at t moment, set b_j (j= 1, 2,… $2n_{ac}+1$) as the ant quantity at j node on the segment Li at t moment. Then, the total ants can be shown in Eq. 10:

$$M_h = \sum_{j=1}^{2n_{ac}+1} b_j \quad (10)$$

Suppose $\tau_{pq}(t)$ indicates the information content left on the path line pq at t moment. At the start moment, the information content on each line is the same. Set $\tau_{pq}(0) = C$ (C is a constant.), $\Delta\tau_{pq} = 0$. During the motion of ant k, the transfer direction is determined according to the information content on each motion configuration line. $P^k_{pq}(t)$ indicates the probability for ant k to transfter from the position p (x'_i, y'_i, z'_g) to q(x'_{i+1}, y'_{i+1}, z'_i) at t moment, as shown in Eq. 11:

$$P^k_{pq}(t) = \begin{cases} \tau^{\alpha}_{pq}(t)\eta^{\beta}_{pq}(t) / (\sum_{q\in N^k_i} \tau^{\alpha}_{pq}(t)\eta^{\beta}_{pq}(t)) & q \in \text{allowed}_k \\ 0 & \text{other} \end{cases} \quad (11)$$

wherein, η_{pq} indicates the visibility of segment pq, pheromone heuristic factor α indicates the relative importance of remaining informaiton ($0 \le \alpha \le 5$) and expected value heuristic factor β indicates the relative importance of visibility. The visibility η_{pq} is a reciprocal of the distance for configuration point's p and q: $\eta_{pq} = 1/d_{pq}$.

UPDATE OF PHEROMONES

With time passage, the pheromones left before disappear gradually. ρ ($0.1 \le \rho \le 0.8$) is used to indicate the duration of pheromones and 1-ρ indicates disappearing degree of pheromones. Apparently, the volatility of pheromones ρ directly affects the overall search ability and convergence rate of ACA. After *m* time units, the ants reach the goal configuration point q_G from the start configuration q_S and the updating equation for pheromones on each path is shown in Eq. 12:

$$\tau_{pq}(t+m) = \rho \cdot \tau_{pq}(t) + \Delta\tau_{pq} \Delta\tau_{pq} = \sum_{k=1}^{M_h} \Delta\tau^k_{pq} \quad (12)$$

$\Delta\tau^k_{pq}$ indicates the pheromones on the unit length trajectory left in the configuration segment pq by No. k ant in this cycle. Set the condition set as e_{pq} for No. k ant to pass through pq in this cycle, the other is $\overline{e}_{pq}$ and it can be calculated according Eq. 13:

$$\Delta\tau^k_{pq} = \begin{cases} Q/F_k & \text{ant}_k \in e_{pq} \\ 0 & \text{ant}_k \in \overline{e}_{pq} \end{cases} \quad (13)$$

Wherein, Q is a constant for pheromone concentration and F_k is an objective function value for No. k ant in this cycle. The main steps for ACA proposed in this study are described as follows:

Step 1: Set the time t and cycle index N_{cycle} as zero, the maximal cycle index as $N_{Maxcycle}$, the information content on each segment as $\tau_{pq}(t)$ = C and $\Delta\tau_{pq}$ = 0. During start, place all ants M_h at the start configuration point q_S

Step 2: Enable all ants. For each ant k, select the configuration points on the next segment by roulette turning method and march it forward according to the probability calculated by Eq. 11

Step 3: Repeat Step 2 until the ant colony reaches the goal configuration point q_G

Step 4: Set t=t+ m and $_1N_{cycle}$++, calculate the path length L_k that each ant passes through and the objective function value F_k and record the current optimal solutions. According to Eq. 12 $\tau_{pq}(t+m) = \rho\tau_{pq}(t)+\Delta \tau_{pq}$:

$$\Delta\tau_{pq} = \sum_{k=1}^{M_h} \Delta\tau^k_{pq}$$

update the information remaining amount on each segment.

Step 5: If the ant colony converges to a motion path or the cycle inde$_1$ N_{cycle} >=$_1$ $N_{Maxcycle}$, then the cycle is over and the optimal motion paths are outputted. Otherwise, Step 2 is executed for further operation

Note: For the selection of ant quantity M_h, two indexes (overall search ability and convergence rate) of the algorithm should be taken into comprehensive consideration. Aiming at FFSR collision avoidance motion planning, a rational selection must be made in terms of overall search ability and convergence rate.

COMPUTER SIMULATION

To verify the algorithm proposed in this study, a simulation research has been made with Visual C++ and OpenGL in PC. Taking dual-arm FFSR with six DOFs as an example, the obstacles are simplified as a circle; the

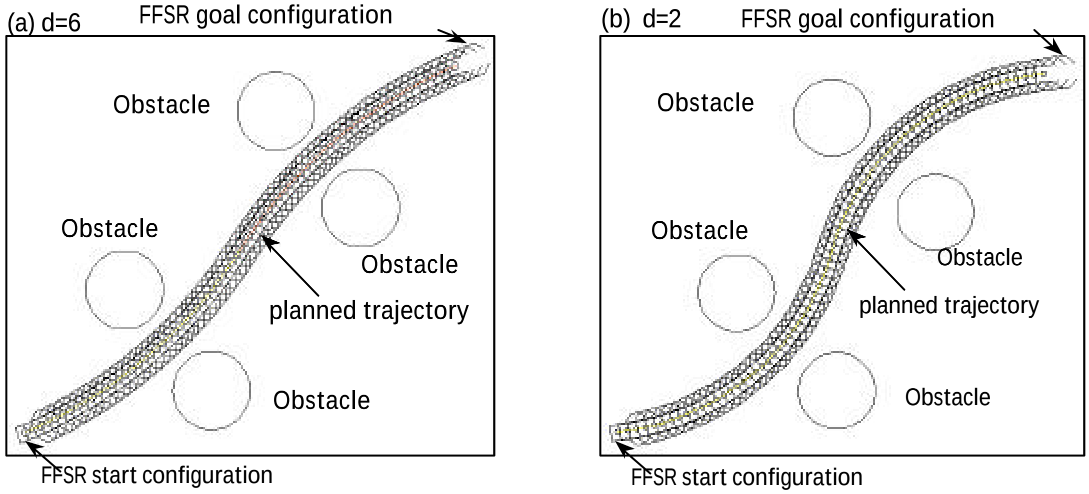

Fig. 2(a-b): Optimized motion trajectory obtained from ACA

Table 1: Parameters of experimental model of dual-arm six DOFs FFSR

	L_0	L^l_1	L^l_2	L^l_3	L^r_1	L^r_2	L^r_3
Length (m)	0.50000	0.40000	0.40000	0.12660	0.40000	0.40000	0.12660
Mass (kg)	5.00000	0.50000	0.50000	0.20000	0.50000	0.50000	0.20000
Inertia moment (kg m^2)	0.20833	0.00667	0.00667	0.00027	0.00067	0.00667	0.00027

segment from start configuration point q_S to the goal configuration point q_S is divided into 40 equal parts. Parameters of experimental model of dual-arm FFSR with six DOFs are showed in Table 1. After experimental confirmation, the optimal parameters for ACA are $\alpha = 1$, $\beta = 5$, $\rho = 0.526$, $Q = 320$. The ant quantity in this study is $M_h = 30$. After K iterative computations (for 242 times), different obstacle avoidance coefficients ä are selected and the optimized trajectory obtained are shown in Fig. 2. In Fig. a, $\delta = 6$ and $\delta = 2$ in Fig. (b). The calculation complexity of this algorithm is O ($M_h \cdot K$), wherein, K is iterations and M_h is the ant quantity.

SUMMARY

ACA is applied in this study to solve the problems in FFSR collision avoidance motion planning and a discussion hereof is conducted. As shown in the simulation results, this algorithm can effectively solve the problems in FFSR collision avoidance which lays a solid foundation for FFSR real-time track planning. In the algorithm, different optimized trajectory can be obtained by adjusting obstacle avoidance coefficient ä which has extended FFSR's adaptability for specific problem. Meanwhile, this algorithm is good for parallel execution and application and features strong robustness. Therefore, ACA has a good application prospect in solving the optimized problems such as FFSR collision avoidance motion planning.

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