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A Chaotic Ant Colony System for Path Planning of Mobile Robot

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Abstract

Aiming at the path planning problem of mobile robot, a chaotic ant colony system was presented. The idea of the algorithm was that first generated chaotic sequences as the initial pheromone matrix and then ant colony traversed grids environment once, pheromone on the path was updated, as the completeness of the pheromone initialization. Pheromone update strategy adopt self-adaptive chaotic disturbance to avoid the search being trapped in local optimum. Grids environment simulated the robot workspace. Through the process of self-organization and chaos, the ant colony found the optimal path in the robot's static environment. Simulation results show that chaotic ant colony system not only enhances the global search capability, but also more effective than the traditional ACS, moreover, it's a novel approach to the robot path planning.

Keywords: *Mobile robot, Path planning, Ant colony system, Chaos, Grids*

1. Introduction

Robotics is an essential part in manufacturing processes automatization. Concerning about mobile robots, they can be very useful in different situations where humans could be in danger or when they are not able to reach certain target because of terrain conditions. The path planning is that the robot can be safe, collision-free and find an optimal motion path from a starting point to goals in an obstacle-covered spatial domain.

Once the robot has the global environmental information available to get a one-time global path planning, we are able to optimize some performance indicators during operation. During the past years, A number of path planning algorithms such as A*, PSO and ACS [1] have been proposed for use in mobile robots. However, those methods are not enough efficient, poor global search capability, and not enough adaptability to complex spatial domain. Despite advantages of better robustness, efficient parallelism, and high efficiency, many scholars have conducted extensive research to improve ant colony algorithms' global search capability [2-4]. Wang Zhangqi [5] applied genetic algorithm to optimization and configuration parameters of the ACO. Simulation results showed that the improved optimal path length significantly less than the ACO. Greedy pheromone update strategy and node-distributed pheromone [6] in ACO reduced the space complexity and improved the convergence speed, however, the algorithm is easy to trap in local optimum. Moreover, authors had not specified the algorithm for complex maps to keep better adaptability.

Chaos is a nonlinear phenomenon widespread in nature. Since chaos is extremely sensitive to the initial value, and aperiodic traverse all states according to their own laws within a certain range, if integrated in ACS, this feature is conducive to the diversity of solutions and the global search capability. There are many reports about the integration of chaos in ACS. By adding chaos disturbance in the local pheromone update, ACS was applied to solve dynamic vehicle routing problem in [7]. AP-PSO [8] constructed two particle swarms. In order to balance effectually the global exploration and the local

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exploitation of swarm, a uniform chaos mutation is proposed by making the best use of the ergodicity, stochastic property and regularity of chaos. At last, comparison simulation shows the effectiveness of this algorithm. Compared to previous works, we propose the chaotic ant colony system (CACS) to analyze path planning in grid environment. The rest of the paper is organized as follows. The state transition rules and the representation and update of pheromone are elaborated in section 2. Section 3 describes chaotic behavior in detail. Introducing chaos on the amount of pheromone update strategy, adaptive adjusts self-organization and chaotic behavior of ant colonies. Experimental results and analysis are presented in section 4. We conclude this paper and outline the future works in section 5.

2. Ant Colony Algorithm for the Mobile Robot Path Planning

The first step of path planning is to establish a two-dimensional environmental model for the spatial domain. A Cartesian coordinate system is established in G provided that the robot is limited in this area. Then we divide G into parallelly quadrilateral units in accordance with the step of robot R_a, where g_{origin} and g_{goal} are the correspond origin and destinations. $SO_1, SO_2, \ldots, SO_p$ indicate the grid barriers, each of which is a set of obstacles. If grid barrier's borders less than one grid cell, we count a grid. After that let all grids label with integers. N_x denotes the number of each row grids, and N_y denotes the number of each column grids. $N = N_x N_y$. The coordinate of a grid labeled *i* is computed by

$$\begin{cases} x_i = \left(\left(i-1\right) \bmod N_x\right) + 1 \\ y_i = N_y - \lceil i/N_x \rceil + 1 \end{cases} \tag{1}$$

where $\lceil i/N_x \rceil$ is an integer which value isn't less than i/N_x. When an ant currently locates at grid g_i, it can detect the environmental information of the area which the center is current g_i and the radius is R_a. Its vision domain $B\left(g_i\left(x_i, y_i\right)\right)$ is the eight neighbor grids surround g_i.

Once ant *k* finds g_{goal}, it crawls back to nest g_{origin} depositing pheromone to mark the route from g_{goal} to g_{origin}. On arriving g_{origin} this ant summons reinforcements to reinforce. Attracted ants crawl on the Path "g_{origin} - g_{goal} - g_{origin}" and also deposit pheromone. Compared to the other route, the evaporation of pheromone will make larger amount of pheromone on the shorter routes. And because larger amount of pheromone have greater influence on ant behavior. The shorter routes will attract more ants, which lead to a further increase in the amount of pheromone around the shorter path. Pheromone have little effect on the ants "chaotic" crawling due to the small amount at the initial stage, so ant colony bias chaotic select path.

But with the increase in the number of search and ants crawling, Pheromone intensity gradually strengthens. The shorter path it is, the greater attraction to ants it has. At the terminal stage, "chaotic" crawl behavior of ants disappears. Throughout the entire search, the ant colony is a process of self-organization, in which the pheromone and the "chaos" work together [9].

2.1. State Transition Rules

(1) Given that robot should keep away from the environmental barriers as far as possible when it avoids obstacles in motion and navigates itself to the destination. When

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ant k, currently located at node i, selects the next node j, we define node j's degree of safety:

$$\Phi(i,j) = \frac{1}{e^{\psi(j)}} \tag{2}$$

where $\psi(j) = n_j - \min_i(n_j)$. n_j denotes the number of obstacle cells in the vision domain of g_j. $\min_i(n_j)$ denotes the minimum number of obstacle cells in the vision domain, node j is all feasible points of current node i.

The larger the exponent $\psi(j)$ is, the more dangerous the next node is, further it has much weaker inspiration effect on ants.

(2) In order to improve the convergence speed, heuristic function of grid j is defined as follows:

$$\eta_j = \frac{1}{\sqrt{\left(x_j - x_{goal}\right)^2 + \left(y_j - y_{goal}\right)^2}} \tag{3}$$

The coordinates of grids g_j, g_{goal} are given by formulae (1).

Ant k, currently located at node i, selects the next node j using the rule (4):

$$j = \begin{cases} \arg\max_{k \in allowed_i} \left(\left[\tau_{ij}\right]^{\alpha} \left[\eta_j\right]^{\beta} \left[\Phi(i,j)\right]^{\gamma} \right), \text{if } q \le q_0 \\ \text{using the probability function (5)} \ \ , \text{if } q > q_0 \end{cases} \tag{4}$$

where q is a random variable uniformly distributed in interval $(0,1)$, q_0 is a user-specified parameter. If $q > q_0$, an ant k selects the next node j with probability P_j^i:

$$P_j^i = \begin{cases} \dfrac{\left[\tau_{ij}\right]^{\alpha} \left[\eta_j\right]^{\beta} \left[\Phi(i,j)\right]^{\gamma}}{\sum_{j \in Wk_i} \left[\tau_{ij}\right]^{\alpha} \left[\eta_j\right]^{\beta} \left[\Phi(i,j)\right]^{\gamma}}, \text{if } j \in allowed_i \\ 0 \qquad\qquad , \quad \text{otherwise} \end{cases} \tag{5}$$

where $Wk_i = \left\{ g \middle| g \in B\left(g_i\left(x_i, y_i\right)\right), g \notin SO \right\}$ is the set of candidate grids connected to grid i, $\left|Wk_i\right|$ denotes the cardinality of set Wk_i. τ_{ij} denotes amount of pheromone from node i to node j. Parameter α is a positive constant used to attract ants. Parameter β is a positive constant used to amplify the influence of the heuristic function. Exponents α, β, γ control the relative importance of pheromone attraction, fast iteration and secure crawl. We keep track of traversed grids that ant k has selected from t_0 to current time t_i in an archive $tabu_k = \left\{ g(t_0), g(t_1), \cdots, g(t_i) \right\}$. When the small value of q_0 is used, most of the ants explore paths more widely according to the probability P_j^i; When the large value of q_0 is used, most of the ants use the candidate grids. For these reasons, q_0 is used to balance exploration capacity and exploitation capabilities of the colony behavior.

2.2. Pheromone Update Rule

The behavior choice of ants is attracted by the pheromone distributed among adjacent arcs. Ants select the next nodes according to the probability. Pheromone left behind in the last cycle influences the behavior of ants by this one step probability. It retains until the next cycle on one hand and vapor over time in this cycle on the other. In this paper, its intensity on each arc needs to be updated at the end of each cycle

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$$\tau_{ij}\left(t\right)=\left(1-\rho\right)\tau_{ij}\left(t-1\right)+\sum_{a=1}^{m_t}\Delta\tau_{ij}^{a} \tag{6}$$

$$\Delta\tau_{ij}^{a}=\begin{cases} Q/c_{\min}, \text{if } \left(i, j\right)\in GlobalBest \\ 0 \quad , \qquad \text{otherwise} \end{cases} \tag{7}$$

where $c_{\min}$ denotes optimal fitness found in this cycle, and m_t is the number of ants having traversed the optimal route. $\tau_{ij}\left(t\right)$ denotes the amount of pheromone remains on the arc between grid g_i and g_j in cycle *t*.

3. Chaotic Ant Colony System

B.J. Cole [10] carefully studied the dynamic behavior of a single isolated ant and ant colony separately by experiment with a static solid-state automatic digital camera. And from the behavior of separately isolated worker, he concluded the following several interesting results.

(1)Behavior of the ant colony is cycle, and activity cycle is roughly 15-37min.

(2)The individual behavior of isolated ant is not cycle. After a relatively long period of inactivity, the activity of a single ant is spontaneous. With the increasing of neighbors, they start synchronization. But only when the numbers of them increase almost the sum of colony members, periodical behavior appear throughout the ant colony.

(3)After carefully analyzed on the data, B.J. Cole concluded that the behavior of single ant was low-dimensional decisive chaotic behavior, while the behavior of entire ant colony was periodical. The time series resulted from single ant behavior's attractor reconstructed, which indicated the dimension of its chaotic attractor is a non-integer 2.43. However, the activities of the entire ant colony had an integer number of dimensions.

3.1. Chaotic Initialization based on Logistic Map

Since chaotic motion has the properties of randomness, ergodicity and initial value sensitivity *etc.*, chaos sequence $\{x_n\}$ is assigned to the pheromone matrix that is corresponding to the amount of pheromone scattered on each adjacent arc.

$$x_{n+1}=\mu x_n\left(1-x_n\right), \mu\in\left(3.57, 4\right] \tag{8}$$

where μ is set 3.9. x_n changes in open interval $\left(0,1\right)$. After completion of a traverse, this search cycle produces a large number of routes. Unlike traditional ant colony algorithm, we choose the comparative betters from them, then update global pheromone matrix. That the completion of algorithm initialization. However, traditional ant colony algorithms assign the same amount of pheromone to all the arcs in the initialization. That always makes the ant colony toughly identifies better paths in a short time. So chaotic initialization based on logistic map can overcome the slow convergence caused by adding chaos.

3.2. Update Pheromone with Chaos Disturbance

In order to avoid ant to run into deadlock, we improve pheromone update rule of traditional ant colony algorithm as the following formula:

$$\tau_{ij}\left(t\right)=\left(1-\rho\right)\tau_{ij}\left(t-1\right)+\sum_{a=1}^{m_t}\Delta\tau_{ij}^{a}+r\left(t\right)\cdot qx_n \tag{9}$$

where q is the mapping coefficient. Selecting the logistic map as pheromone intensity disturbance is conducive to jump over local optimum and increase the diversity of

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solutions. Coefficient $r(t)$ is similar to sigmoid function.

$$r(t)=1-\frac{1}{1+\exp(-0.095t+4)} \tag{10}$$

variable t said search cycle. We select the factor 0.095 so as to make $r(t)$ playing an effective role in the disturbance. At the early stage of the evolution, since chaos role is larger, we use its traversal to improve global search capability. At the late stage of the evolution, the larger self-organization will ensure that the algorithm convergent rapidly.

4. Simulation of Two-Dimensional Grid Environment

In this section, we describe the implementation of the algorithm and analyze the comparative experiment results.

4.1. Algorithm Steps

In this paper, CACS and experimental procedure is as follows:

Step 1：Setting each of user-specified parameters. The data structures store the results of CACS. After solve equation (8) to generate chaotic sequence, we assign it to matrix $(\tau_{ij})_{N\times N}$. Then implement Step 2-4 to get initial pheromone matrix;

Step 2：Ant k $(\mathrm{k}=1,2,\cdots,\mathrm{m})$ crawls from grid g_{origin}, and the g_{origin} is stored in archive $tabu_k$. Then follow (4), (5) transfers one step and the current grid j is stored in archive $tabu_k$, updating the set of nodes to be selected by each ant in next step;

Step 3：Combining the two aspects of information that heuristic information of current grid and the amount of pheromone on the arc between the neighbor grids together, we obtain feasible routes from origin to destinations;

Step 4：At the end of this search cycle, we compare all the routes' length, and implement equation (8) to generate chaotic sequence. Then update pheromone matrix according to equation (9). By $n=n+1$, the algorithm enters the next search cycle;

Step 5：If $n<NC_{\max}$, where $NC_{\max}$ is the user-specified maximum number of iterations, we empty the archive $tabu_k$ $(\mathrm{k}=1,2,\cdots,\mathrm{m})$ and go to step 2 to continue a new cycle. Else if $n=NC_{\max}$, stop.

4.2. Comparison Simulation Analysis

To verify the effectiveness of CACS, we have conducted a lot of simulation experiments and the map is divided into 20 × 20 grids. By means of the adjustment, the parameters were set as follows: heuristic factor $\alpha=1$, factor $\beta=5$, pheromone evaporation factor $\rho=0.01$, compensation intensity $Q=1$, $q_0=0.15$ and the number of ants $m=50$. The experimental results are shown in Figure 1 and Figure 2. Figure 1 depicts the convergent curve of CACS in the grid environment of Figure 2. The solid line in Figure 2 is a global optimal path of CACS and the dashed line is the optimal path in [11]. Figure 1 illustrates the good performance of the diversity of solutions and global convergence. The chaotic initialization and update pheromone with chaos don't increase the complexity of algorithm.

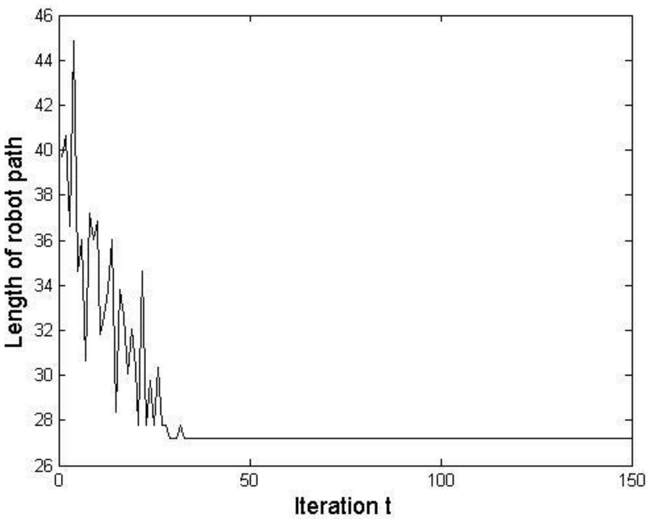

Figure 1. Convergence Curve of CACS during Evolutionary Process

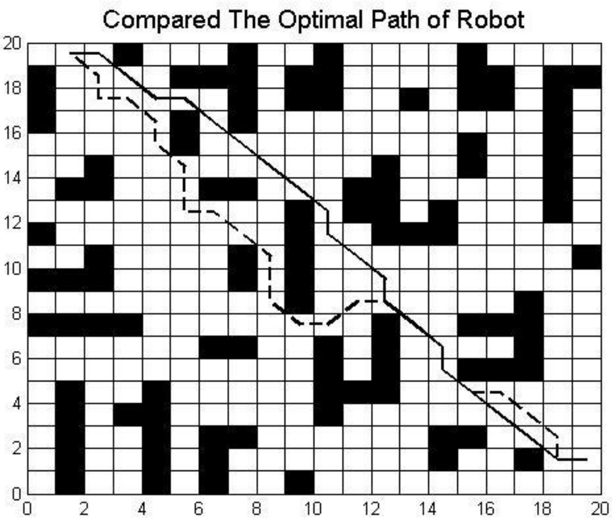

Figure 2. CACS and Algorithm in [11] Solve for the Optimal Paths

Table 1 compares the simulation results of CACS and the one in [11]. Compared with algorithm in [11], CACS convergent even less average iterations, but significantly obtain higher precise solutions.

Table 1. Comparison of Two Algorithm Results

	length of optimal path	convergence iterations
CACS	27.2132	46
algorithm in [11]	30.9705	66

4.3. Multi-Objective Path Planning

If there are multiple destinations in the spatial domain of robot, it's one search period when ant colony reaches each goal grid in turn. Then we use the grid environment of Figure 4 to test the CACS (algorithm 1), ACS (algorithm 2) and the algorithm in [12] (algorithm 3). Goal grid are $G1 = 341$、$G2 = 33$、$G3 = 715$、

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$G4=1089$. By means of the adjustment, the parameters were set as follows: heuristic factor $\alpha=1$, factor $\beta=5$, pheromone evaporation factor $\rho=0.02$, compensation intensity $Q=2.5$, $q_0=0.15$ and the number of ants $m=50$. The RED line is the simulation result of algorithm 1 and the BLUE line is the simulation result of algorithm 2 in Figure 3. The solid line depicted an optimal path found by algorithm 1 and the dashed line depicted an optimal path found by algorithm 3 in Figure 4. From Figure 3, it could be observed that algorithm 2 is easy to fall into local optima. CACS improves the global search ability of ant colony algorithm effectively; Figure 4 shows that for multi-objective path planning algorithm 1 can also find the global optimal path which is safer than one of algorithm 3.

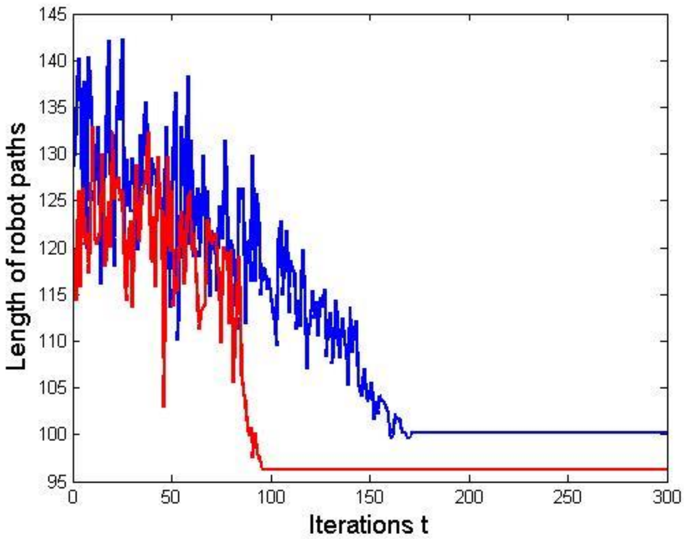

Figure 3. Convergence Curves of Algorithm 1 and Algorithm 2 during Evolutionary Process

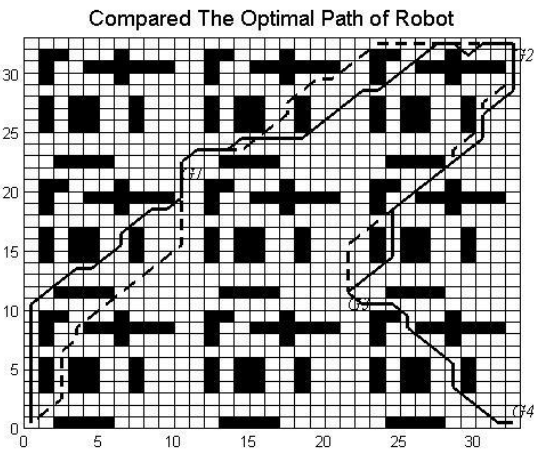

Figure 4. Optimal Path of Algorithm 1 and 3

Table 2. Comparison of Three Algorithm Results

	length of optimal path	convergence iterations
algorithm 1	96.3259	less than 100 iterations
algorithm 2	101.9827	about 150 iterations
algorithm 3	>96.3259	about 110 iterations

From Table 2, we can see that algorithm 1 is significantly better than algorithm 3 and the optimal path is shorter. The chaotic behavior of the algorithm 1 is conducive to avoid falling into local optimum.

5. Conclusions

In this study, we propose the chaotic ant colony system for robot path planning in order to overcome the defect of ACS being easy to fall into local optimum. We improve the ACS, in which more complete heuristic information for selecting path are considered, and the introduction of chaos not only corresponds with process features in ants behavior, but also improves self-organization process of the traditional ACS. Simulation results show that comparing with ACS, CACS has the stronger global search capability, and can maintain good adaptability even in the case of multi-objective path planning. The effectiveness of CACS is superior to the ACS. This paper presents a new way for the robot path planning. The future work is as follow:

1) Analyzing the effects of parameters in CACS, and attempting to find the rules to make the algorithm of a better generality.

2) Developing better strategies of updating pheromone and selecting path to improve the searching efficiency.

3) Further researching the chaotic dynamics of ant colony.

6. ACKNOWLEDGEMENTS

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