Research on intelligent mobile robot full coverage path planning

Guobiao Fei, Fenggang Liu*
School of Artificial Intelligence, Wuchang University of Technology, Wuhan 430223, Hubei, China

*Corresponding author: fenggangliu@wut.edu.cn

Abstract. Aiming at the full coverage path planning problem of intelligent robot, a local chaos evaluation planning method is proposed. Considering the randomness and unpredictability of the mobile robot, a four-dimensional chaotic system with feedback control variables is designed. The path planning model is established by fusing the system with the robot motion model. At the same time, the coupling control parameters are introduced to adjust the system error. According to the initial coordinates and chaotic initial state parameters of the robot, the moving path points can be calculated by differential discretization. Considering the local optimal solution of the path planning, the mobile space of the robot is meshed, and the dynamic mesh activity value is calculated according to the excitation. The mesh activity is used to divide the mobile path planning, and then the local path and angular displacement changes are obtained. At the same time, the corresponding index evaluation is designed for local path planning to correct the planning results. The simulation results show that the proposed local chaos evaluation planning method has a good effect of full path coverage, and obtains lower path repetition rate, moving distance and path planning time, which effectively improves the mobile efficiency and control stability of the robot.

Keywords: Intelligent robot, Local path planning, Chaotic system, Index evaluation, Full coverage.

1. Introduction
The development of intelligent robots has promoted their applications in geological exploration, military detection, regional cleaning and many other aspects [1]. With the expansion of the range of use, the performance requirements for intelligent robots are becoming more and more complex, and the full coverage path planning of intelligent robots is the key point [2]. It is required to complete the full coverage of the task in the established target space [3]. For example, the cleaning robot in life needs to complete the task of cleaning the ground through the most reasonable path planning scheme. For many fields, such as business and military, full coverage path planning has a critical impact on the final mission execution results. For example, for battlefield clearance, mission path coverage and completion efficiency cannot be ignored.

In the process of moving path planning, robots are faced with serious randomness and unpredictability [4], which is exactly in line with the characteristics of chaotic systems. Chaotic algorithm shows good
performance in random initial value and traversal processing [5]. Combining it with path planning is helpful to improve the overall performance of full coverage path planning. Literature [6] ~ [8] all introduced chaotic system into robot control. It can be seen from the research results that the low-dimensional chaotic system still has defects in traversal coverage, which can be solved by integrating other methods, but the overall performance of the method is not improved very much. In addition to introducing chaotic algorithm, local search strategy is also recognized by existing researches because it can effectively avoid obstacles and prevent the occurrence of dead zones. Literature [9] designed local coverage based on West-Move First, and completed full coverage search combined with backtracking. In Literature [10], the robot's moving area is divided into grids, and the obstacles, through grids and non-through grids are marked, and the reliability is used for real-time adjustment. In literature [11], the potential field force was divided into grids, and the planning task was realized by using the cow-farming mechanism. Considering the characteristic similarity between the chaotic system and the robot motion system, and based on the research results of the existing low-dimensional chaotic system, this paper designs a four-dimensional chaotic system according to Lorenz-like to improve the path coverage and process the randomness of the path. Due to the increase of Lyapunov exponent, and the number of Lyapunov exponent can reflect the merits and demerits of chaotic system, lower dimensional chaos will show obvious advantages in the face of unpredictable situations. The fourth dimension of the designed chaotic system is the feedback control parameters, which can be used to predict the complex behaviors after the fusion with the robot dynamic model. In addition, considering the local characteristics of paths and the advantages of local search strategy, this paper designs a local path planning strategy with index evaluation feedback. In the moving region of the robot, the environment of each region is different, which has different influence on the path planning model. Here, grid partitioning is adopted, active values of all grids are marked, and active values of all grids are dynamically adjusted according to the connections between grids, so as to guide path shunt and angular displacement changes.

2. Path planning model based on four-dimensional chaos

2.1. Four-dimensional chaotic system

According to Lorenz-like [12], a four-dimensional chaotic system with feedback control variable W is designed here, which is described as follows:

\[
\begin{align*}
\dot{x}_1 &= \mu_1 (x_2 - x_1) \\
\dot{x}_2 &= \mu_2 x_1 - x_1 x_3 - \mu_3 x_2 + W \\
\dot{x}_3 &= x_1 x_2 - \mu_4 x_3 \\
\dot{W} &= -\mu_5 x_1 - \mu_6 W
\end{align*}
\]  

(1)

Among them, \( \mu_1 \sim \mu_6 \) are positive coefficients. The corresponding chaotic behavior is obtained by Lyapunov exponent, so as to obtain the degree of convergence and divergence of the system. Under the \( (\mu_2 - \mu_3 - \mu_5/\mu_6) \mu_4 > 0 \) condition, the four-dimensional chaotic system has three equilibrium points: \( B_0(0, 0, 0, 0), B_1(\epsilon, \epsilon, \mu_2 - \mu_3 - \mu_5/\mu_6 - \mu_5/\mu_6) \) and \( B_2(-\epsilon, -\epsilon, -\mu_2 - \mu_3 - \mu_5/\mu_6, \mu_5/\mu_6) \), where parameters \( \epsilon = \sqrt{(\mu_2 - \mu_3 - \mu_5/\mu_6)\mu_4} \). The Jacobi matrix of the system is set as follows

\[
A(\dot{x}_1, \dot{x}_2, \dot{x}_3, W) = \begin{bmatrix}
-\mu_1 & \mu_1 & 0 & 0 \\
\mu_2 - \dot{x}_3 & -\mu_3 & \dot{x}_1 & 1 \\
\dot{x}_2 & -\mu_4 & 0 & 0 \\
0 & -\mu_5 & 0 & -\mu_6
\end{bmatrix}
\]  

(2)
Through the equilibrium point and Jacobi matrix, the corresponding characteristic equation is obtained:

\[
\begin{align*}
\mu_1 + \mu_3 + \mu_4 + \mu_6 &= a \\
- \mu_1 \mu_2 + \mu_1 \mu_4 + \mu_3 \mu_4 + \mu_1 \mu_6 + \mu_3 \mu_6 + \mu_4 \mu_6 &= b \\
- \mu_1 \mu_2 \mu_3 \mu_4 - \mu_1 \mu_3 \mu_5 \mu_4 + \mu_1 \mu_3 \mu_6 \mu_4 + \mu_1 \mu_5 \mu_6 \mu_4 + \mu_3 \mu_5 \mu_6 &= c \\
\mu_1 \mu_4 \mu_5 - \mu_1 \mu_2 \mu_4 \mu_6 + \mu_1 \mu_3 \mu_4 \mu_6 &= d \\
\end{align*}
\]

(3)

If the condition \((\mu_2 - \mu_3 - \mu_5/\mu_6) \mu_4 \leq 0\) holds, there is only one equilibrium point \(B_0(0,0,0,0)\) in the four-dimensional system. In this case, the characteristic equation of \(B_0(0,0,0,0)\) is described as follows:

\[
(\lambda + \mu_4) (\lambda^3 + E_1 \lambda^2 + E_2 \lambda + E_3) = 0
\]

(4)

\(E_1 = \mu_1 + \mu_3 + \mu_6, E_2 = -\mu_1 \mu_2 + \mu_1 \mu_3 + \mu_3 \mu_6 \circ E_3 = \mu_1 \mu_5 - \mu_1 \mu_2 \mu_6 + \mu_1 \mu_3 \mu_6\)

The determinant can be solved accordingly:

\[
\begin{vmatrix}
E_1 & 1 & 0 \\
E_3 & E_2 & E_1 \\
0 & 0 & E_3 \\
\end{vmatrix}
\]

(5)

After the analysis of determinant, we can see that \(E_3 < 0\). That is, when \(\mu_5 + \mu_3 \mu_6 < \mu_2 \mu_6\), \(\phi_2\) and \(\phi_3\) are different signs, indicating that the point \(B_0(0,0,0,0)\) is unstable. When \(\mu_5 + \mu_3 \mu_6 \neq \mu_2 \mu_6\), the condition \(E_1 > 0, E_1 E_2 > E_3, \mu_5 + \mu_3 \mu_6 > \mu_2 \mu_6\) is simultaneously satisfied, then \(B_0(0,0,0,0)\) point is locally stable.

2.2. Chaotic path planning

In the process of intelligent robot moving, it is assumed that the linear velocity is \(v\) and the angular velocity is \(v \omega(t)\). The angular displacement is \(\theta(t)\). The kinematic equation is described as follows:

\[
\begin{align*}
\dot{x} &= v \cdot \cos(\alpha \cdot \theta(t)) \\
\dot{y} &= v \cdot \sin(\alpha \cdot \theta(t)) \\
\dot{\theta} &= \omega(t)
\end{align*}
\]

(6)

Among them, \(\dot{x}, \dot{y}\) successively represents the abscissa and ordinate position within the moving range; \(\alpha\) represents the adjustment factor of angular displacement. According to equation (6) and four-dimensional chaotic system, the angular displacement is set as chaotic variable \(x_1\), and the chaotic path planning model is established as follows:
Where, $\dot{x}, \dot{y}$ represents the moving position when iterating for $n$ generations. When the chaotic system achieves synchronization control, the angular displacement is set as the chaotic synchronization variable $y_1$. At this point, the path planning model is established as follows:

$$
\begin{align*}
\dot{x}_1 &= \mu_1 (x_2 - x_1) \\
\dot{x}_2 &= \mu_2 x_1 - x_1 x_3 - \mu_3 x_2 + w \\
\dot{x}_3 &= x_1 x_2 - \mu_4 x_3 \\
\dot{w} &= -\mu_5 x_1 - -\mu_6 w \\
\dot{x}_a &= v \cdot \cos (\alpha \cdot x_1) \\
\dot{y}_a &= v \cdot \sin (\alpha \cdot x_1)
\end{align*}
$$

$$
(7)
$$

Wherein, $\mu_1, \mu_2, \mu_3, \mu_4, \mu_5, \mu_6$ are control parameters of $x, y$ in turn. Based on path planning models (7) and (8), discretization is adopted through differentiation. The robot starting coordinate $(x_0, y_0)$ and the four-dimensional chaotic starting state parameter $(x_{10}, x_{20}, x_{30}, w_0)$ are used as the starting input of the planning model, so that the moving path point $(x_n, y_n)$ can be calculated. In the iterative calculation process, the optimal solution $G$ will be obtained in each round, and chaos search will be carried out for the surrounding area of $G$ in the following manner:

$$
\begin{align*}
\dot{y}_1 &= \mu_1 (y_2 - y_1) + O_{y_1} \\
\dot{y}_2 &= \mu_2 y_1 - y_1 y_3 - \mu_3 y_2 + w + O_{y_2} \\
\dot{y}_3 &= y_1 y_2 - \mu_4 y_3 + O_{y_3} \\
\dot{w} &= -\mu_5 y_1 - -\mu_6 w + O_{y_4} \\
\dot{x}_a &= v \cdot \cos (\alpha \cdot y_1) \\
\dot{y}_a &= v \cdot \sin (\alpha \cdot y_1)
\end{align*}
$$

$$
(8)
$$

Wherein, $O_{y_1}, O_{y_2}, O_{y_3}$ and $O_{y_4}$ are coupling control parameters, which are adjusted according to the system error. Assume that the error vector is $\dot{e} = [e_1, e_2, e_3, e_4]$, then the coupling control parameters are adjusted as follows:

$$
\begin{align*}
O_{y_1} &= \frac{1}{\sigma} e_2 \\
O_{y_2} &= \frac{1}{\sigma} (-e_1 - e_4 - \tau x_1 x_3 + \sigma y_1 y_3) \\
O_{y_3} &= \frac{1}{\sigma} (-e_3 + \mu_1 x_1 x_3 - \sigma y_1 y_3 + \mu_3 (\sigma - \tau)) \\
O_{y_4} &= \frac{1}{\sigma} (-e_3 + \mu_4 e_2)
\end{align*}
$$

$$
(9)
$$

Where, $\sigma, \tau$ represents the control parameters of $x$ and $y$ in turn. Based on path planning models (7) and (8), discretization is adopted through differentiation. The robot starting coordinate $(x_0, y_0)$ and the four-dimensional chaotic starting state parameter $(x_{10}, x_{20}, x_{30}, w_0)$ are used as the starting input of the planning model, so that the moving path point $(x_n, y_n)$ can be calculated. In the iterative calculation process, the optimal solution $G$ will be obtained in each round, and chaos search will be carried out for the surrounding area of $G$ in the following manner:

$$
g = G_{sl} + \xi^s \times y_{i+1} \times rand^3
$$

$$
(10)
$$
Where \( y_{i+1} = 1 - 2y_i \); \( \xi \) represents the attenuation factor, which is used to control the size of the area around the optimal solution.

3. Local path planning strategy
In the local path planning strategy, the local grid is used to divide the robot's mobile space, and all the grids are given corresponding active values. For any of the meshes, only the adjacent meshes are assumed to be connected to form a local connection space. The dynamic description of grid activity value is as follows:

\[
\frac{d_s}{dt} = -\eta_1 x_1 + (\eta_2 - x_1) (R_i^+ \sum_{i=1}^{m} w_{i,j} \delta_{i,j}) - (\eta_3 - x_1) R_i^-
\]  

(11)

Where, \( m \) is the total number of grids divided by moving space; \( \eta_1 \) is the attenuation coefficient; \( \eta_2 \) is the maximum activity threshold; \( \eta_3 \) is the minimum activity threshold; \( w_{i,j} \) is the weight of grid \( i \) influenced by grid \( j \). \( R_i^+ = \max\{R_i, 0\} \) is positive excitation; \( R_i^- = \max\{-R_i, 0\} \) is the reverse excitation. Grid activity plays a diverging role in the process of moving path planning. When grid \( I \) is the target in path planning, let \( R_i = -r (r \gg \eta_2) \); If grid \( i \) is the obstacle encountered in path planning, then let \( R_i = r (r \gg \eta_2) \); Otherwise, I'm going to set \( R_i \) equal to 0. When calculating the weight between grids, the Euclidean distance \( d \) between grids is adopted to determine. The range of grids with adjacent connections is taken as the constraint, and the maximum number of connection grids \( 8 \) is also added to the constraint condition. When the Euclidian distance between grids \( d \) is not within the limited range, its influence weight is set to zero. When the Euclidian distance \( d \) between grids is within a limited range, make the weight \( w_{i,j} = s / d \), and \( s \) is a positive coefficient. The movement path after shunting is described as follows:

\[
p_s \leftrightarrow x_{p_s} = \max\{x_j, j = 1, 2, \cdots, q\}
\]  

(12)

\( p_s \) represents the grid target to be moved next time, where \( q \) represents the total number of connections with the grid. Due to the limitation of local strategy, in order to achieve full coverage path, \( \theta(t) \) item was added when the subsequent grid target was determined, and path planning was rewritten as:

\[
p_s \leftrightarrow x_{p_s} = \max\{x_j + \theta(t), j = 1, 2, \cdots, q\}
\]  

(13)

Where, \( \beta \) represents the angular displacement control coefficient, which can control the magnitude of the direction change, and the maximum threshold value limiting the angular displacement change is \( \pi \). Assuming that the robot was located in grid \( p_1 \) in the previous time, \( p_0 \) in this time, and may move to grid \( p_j \) in the next time, the variation of angular displacement is calculated as:

\[
\Delta \theta_j = \left| \arctan \left( \frac{y_{p_j} - y_{p_0}}{x_{p_j} - x_{p_0}} \right) - \arctan \left( \frac{y_{p_i} - y_{p_0}}{x_{p_i} - x_{p_0}} \right) \right|
\]  

(14)

4. Coverage path evaluation
To evaluate the calculated path is to measure the quality of path planning and select the optimal evaluation path as the final result. Because this paper adopts the local path planning, so the evaluation is also based on the local path. The evaluation indexes are path coverage and smoothness. In the coverage analysis, we should consider the local coverage and keep the balance of the local coverage. In the connection region formed by any grid, the coverage of local path \( l_i \) over the region \( s_i \) can be expressed as follows
\[
C_{\text{sub}}(l_i, s_i) = \int_{h_i} f(l_i, h) \varphi(h) \, dh
\]  
(15)

Where \( h \) is the corresponding grid; \( f(l_i, h) \) indicates that the path \( l_i \) passes through the \( h \) grid in the region; \( \varphi(h) \) Represents the corresponding path density. Because there is a certain relationship between the coverage and the length of the path in the local area, the path length \( L_i \) is introduced to optimize the local coverage:

\[
\hat{C}_{\text{sub}}(l_i, s_i) = \frac{1}{L_i} \int_{h_i} f(l_i, h) \varphi(h) \, dh
\]  
(16)

Considering that when the robot moves, it should try to avoid excessive angular displacement changes and keep the path as smooth as possible, so the smoothness evaluation is constructed by using the angular displacement difference between the two movements:

\[
C_{\text{sub}}(l_i) = \begin{cases} 
\frac{\pi}{\theta^2} & |\theta_{i+1}(t) - \theta_i(t)| > \theta_i \\
\pi^2, & \text{other}
\end{cases}
\]  
(17)

Where, \( \theta_i \) is the upper limit of the angular displacement that does not affect the movement or operation of the robot; \( \theta_{i+1}(t) \) and \( \theta_i(t) \) are respectively the angular displacements of the last and the current movement planning. By integrating coverage and smoothness and controlling their weights in the evaluation respectively, the final evaluation function is obtained:

\[
C_{\text{result}}(l_i, s_i) = w_s \hat{C}_{\text{sub}}(l_i, s_i) + w_t C_{\text{sub}}(l_i)
\]  
(18)

Among them, \( w_s \) and \( w_t \) represent the weight of coverage and smoothness in turn.

5. Simulation and result analysis

According to the local path planning strategy proposed in this paper, the mobile space of the robot is divided into \( 20 \times 20 \) The initial state of the chaotic control system is set as \( (x_{1,0}, x_{2,0}, x_{3,0}, w) = (0,10,1) \). In order not to interfere with the initial moving state of the robot, the initial position of the robot is set as \( (x_0, y_0) = (2,2) \), and the maximum number of iterations is 500.

For different mobile space environments, local chaos is simulated to evaluate the actual effect of full coverage path planning. Because the space environment adopts random deployment, its complexity can be adjusted arbitrarily. Here only two scenarios are listed, and the path planning results are shown in Fig. 1.

From the path planning in different mobile spaces, it can be seen that the robot can recognize obstacles and space boundaries well and avoid effectively no matter what kind of scene. At the same time, the mobile path keeps good angular displacement and the number of turns, there is no large turning angle and too many turns, which is conducive to the balance control and mobile efficiency of the robot. In the divided grid area, the planning path achieves good coverage effect, and all grids except obstacles are covered, and there is no serious repeated path. The experimental results show that the path planning method has good control stability, obstacle avoidance, area coverage, path repeatability and smoothness.
In order to better verify the actual effect of this method, the performance comparison is carried out by using the methods in literature [8] and literature [9], in which the chaos algorithm is introduced in literature [8] and the backtracking method is introduced in literature [9]. The coverage rate, repetition rate, path length and other important performance of each method are numerically verified. The final results of the experiment are obtained by calculating the average value of the results in 20 different moving spaces, as shown in Table 1.

**Table 1. Performance comparison of path planning**

| method          | path length | Number of turns | Maximum angular displacement | Repetition rate | Coverage |
|-----------------|-------------|-----------------|------------------------------|-----------------|----------|
| Text method     | 394         | 112             | $0.75\pi$                   | 1.15%           | 100%     |
| Reference [8]   | 445         | 209             | $\pi$                       | 5.49%           | 100%     |
| Reference [9]   | 427         | 178             | $\pi$                       | 3.83%           | 100%     |

From the performance comparison of path planning, the mobile space coverage rate of the three methods is 100%, which meets the requirements of full coverage path. However, from the point of view...
of the moving distance of the whole regional space, this method is 394 units, which is 51 units and 33 units shorter than the other two methods respectively. At the same time, the number of turns in the whole process is only 52, which is significantly reduced compared with the other two methods. The shortening of the mobile path distance and the reduction of the number of turns mean that the time and power consumption of the task execution of the intelligent robot can be reduced in the path planning. From the comparison of the maximum angular displacement, it can be concluded that this method does not need large turning angle and large speed adjustment in path planning, which is conducive to the smooth control of the robot and the mobile efficiency of the robot. In addition, from the analysis of path repetition rate, this method is only 1.15%, which is significantly lower than the other two methods. It fully shows that this method has a better performance advantage in full coverage path planning, and achieves the full coverage requirement with the lowest possible repetition rate. The advantages of this method are based on the combination of robot motion model and chaos algorithm. The linear velocity, angular velocity and angular displacement are taken as the control variables of chaos synchronization to solve the problem. The random unpredictability of chaos algorithm is brought into full play, and the topological ergodicity of chaos system is also effectively utilized. In addition, local path planning and local path evaluation based on grid activity value design make the overall path planning effect more delicate and avoid large-scale unreasonable path. Through local planning and index evaluation, the rationality of planning path can be judged timely and accurately.

Finally, five mobile space environments are randomly configured, and the path planning time of each method is compared through simulation, and the results are shown in Figure 2. From the data in the figure, the influence of the above experimental results on the path planning time is verified. This method has the shortest robot moving time and effectively improves the task execution efficiency of intelligent robot.

![Figure 2. Comparison of path planning time](image)

### 6. Concluding remarks

In order to improve the overall performance of full coverage path planning for intelligent robot, a local chaos evaluation planning method is proposed. The characteristic equation and equilibrium point of a four-dimensional chaotic system are analysed. On this basis, the motion equation of the robot is fused, and the path planning model is established. After the chaotic system achieves synchronization control, the position coordinates of the moving path are obtained by iterative calculation. Based on the local idea, the mobile space of the robot is meshed, and the path strategy is judged according to the grid activity value, and the corresponding evaluation index is designed for the local path planning. The simulation results show that the proposed full coverage path planning method can effectively shorten the moving distance and time of the robot, maintain better balance control, achieve full coverage of the path and significantly reduce the path repetition rate.
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