Deterministic iterative path planning algorithm based on node storage structure

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Abstract. Aiming at the problems of low efficiency of path planning, a new node storage structure is introduced and the search method is optimized to improve the deterministic iterative path planning algorithm. First, the number of antibodies is determined based on the connectable starting path point, when generating the initial antibody with the inspiration of the optimal angle vaccine. Then, the connectable path point of the starting point is treated as the root node to rebuild the new path with path filtering by means of the optimal path fit value. The initial optimal antibody is used as the screening criterion to avoid invalid path point mutation with 100% confidence conditions. Finally, a path point is a basic unit that forms the connection network and stores the parameter information that reaches it. After the algorithm iteration, the optimal path is output. In different maps, the algorithm in this paper is compared with others. The results show that the algorithm effectively reduces the computational cost and has better adaptability to different maps.

Keywords: Immune Mechanism; Deterministic; Storage Structure; Restricted Search.

1. Introduction
Path planning is one of the important issues in the navigation research of mobile robots, which aims to plan the collision-free path from the starting position to the target position in the working environment with multiple obstacles [1]. At present, they are often used to construct static environment models, which include raster, tangent, and Voronoi diagram [2-5]. Because the path in the tangent diagram is shorter and more efficient, the tangent graph method is used to construct the environment model, when the obstacle buffer zone is set to ensure the safety of the robot movement. Common path planning algorithms mainly include A* algorithm, Dijkstra algorithm, Artificial potential field algorithm, and other traditional algorithms [6-8]. Ant colony algorithm, Genetic algorithm, Particle swarm optimization algorithm, and other bionic algorithms [9-11]. Duan [12] used an artificial immune algorithm for path planning in a viewable environment. Experimental results show that the algorithm
can successfully solve the optimal path in a simple environment. Liu [13] guided pheromones to diffuse in the direction of potential field force in the ant colony algorithm, which enhanced the local optimization ability of the algorithm. Zhang [14] introduced a lone Wolf escape strategy into the ant colony algorithm to build a pheromone updating mechanism, which helped the algorithm jump out of the local optimum and improved the searching ability of the algorithm. Yuan [15] improved A* algorithm to optimize the key points of the path, breaking the restriction of the grid on the path and realizing path smoothing. The fusion and improvement of the algorithm accelerate the speed of evolution and iteration, so it has positive significance for path quality. However, the misleading problem of the one-search algorithm and the uncertainty and redundancy of the iterative evolutionary algorithm has not been solved completely. A new node storage structure and restrictive search rules are proposed based on the deterministic search characteristics of the traditional algorithm and the iterative optimization idea of the bionic algorithm. This is an improvement in the algorithm in literature [1] to improve its computational efficiency.

2. model and problem description

The tangent graph environment model is the basis of path planning. Fig. 1(a) is the basic environmental information. A black buffer between the black obstacle and the boundary line is set to avoid the collision between the robot and the obstacle, so the mobile robot can be regarded as a particle for path planning. After the generation of the tangent line diagram, each tangent line forms the actual driving path of the mobile robot. After removing each obstacle as shown in Fig. 1(b), the tangent line diagram can be transformed into a phase-free diagram that contains the starting point, ending point, and boundary of the obstacle. In addition, the change of the starting point and the ending point does not affect the connection relationship between other path points.

(a) Basic environmental information
(b) Tangent undirected graph

Fig. 1 Environmental model

Assuming that the path is composed of \( n \) points, Euclidean distance is used to evaluate the path quality in an undirected graph. The algorithm target function can be expressed as:

\[
f = \min \sum_{i=1}^{n-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}
\]  

(1)

3. Node storage structure and dynamic restrictive mutation

3.1. Node storage structure

The literature [1] proves the effectiveness of forwarding antibody construction and reconstruction mutation. The algorithm extends the secondary node, which is the connectable point of the initial node, and reaches the endpoint at the optimal Angle. Paths with the same path fitness value do not affect the final solution quality, only one forward node information can be kept. The node information required for path variation is stored by the back node.

As shown in Fig. 2, the search process of the algorithm is composed of the initial selection stage, the extension and mutation stage, and the termination target selection stage. The connectable pathway at the initial point is extended to the endpoint along with the vaccine inspiration. In this process, the path points of the extension phase have only one backward join point as shown by the solid line in Fig.
but path point variations cause their backward join points to gradually increase as shown by the dashed line in Fig. 2. The path information storage format is shown in Fig. 3.

The information storage of each path point is divided into six parts. Based on the current path point information, the algorithm stores its front and back path points and marks the distance traveled to the path point. In addition, 0 and 1 are used to mark whether the node has been extended or mutated.

3.2. Dynamic restrictive mutation

The search process of the algorithm is divided into the initial expansion stage and the mutation stage. The algorithm flow chart is as follows:
The specific steps of the path information update are as follows:

Step 1: The set of root nodes is selected with the total number of $k_2$, $j = 1$.

Step 2: The $j$th root node is selected, which contains $k_i$ subsequent path points, $i = 1$.

Step 3: The path point of $i$ is selected. The fitness is calculated to reach this path point, if the current fitness value is superior to the original fitness value, the path distance and forward node information are updated, and their connectable path points are placed into the subsequent update root node-set.

Step 4: If $i$ is equal to $k_i$, then go Step 5, otherwise $i = i + 1$ and go Step 3.

Step 5: If $j$ is equal to $k_j$, then go Step 6, otherwise $j = j + 1$ and go Step 2.

Step 6: The algorithm deletes the target point in the subsequent root node, and terminates if the set is empty, otherwise go to Step 1.

4. Design of university education intelligent agent
4.1 Experimental analysis

The algorithm in this paper is used for experimental simulation in Windows 10; MatlabR2018a; processors Intel (R) Core (TM); i5-4750 4 GB of memory computer platforms.

4.1 Algorithm adaptability

In order to verify the adaptability of the algorithm in different maps, this algorithm is compared with DIA in [1], AIA in [12], and WAH in [14]. These algorithms were used to conduct solving experiments of 1000 times. The adaptive value change curves of the IDIA algorithm and DIA algorithm basically coincide, only the IDIA adaptive value change curve is displayed. The results and the data comparison of other algorithms are as follows:
As shown in Fig. 5, the IDIA algorithm achieves deterministic solution in fewer solving algebras than WAH and AIA under the condition of searching for the optimal solution. Therefore, IADA effectively reduces the set of redundant evolutionary algebra. AIA and WAH were set to iterate for 50 generations in the experiment, the average time of each iteration of the IDIA algorithm was about 160% that of the AIA algorithm and WAH algorithm. However, due to the small number of total iterations required, the overall calculation time of the IDIA algorithm is approximately 16% that of the AIA and WAH algorithms. As described in Tab. 1, a significant decrease in the success rate of AIA and WAH algorithms results in unstable final output solutions in complex environments. IDIA is always able to output effective solutions with more practical application value.

4.2. Algorithm analysis
As shown in Tab. 1, IDIA has higher search efficiency than DIA. IDIA is improved by DIA, in order to analyze the differences between the two algorithms in the search process, the path point variation, and expansion of the two algorithms were analyzed experimentally. The specific results are shown in Fig. 7:

![Fig. 5 Optimal path](image)

![Fig. 6 The path distance curve](image)

| Simulation environment | IDIA time(s) | IDIA rate | DIA time(s) | DIA rate | AIA time(s) | AIA rate | WAH time(s) | WAH rate |
|------------------------|-------------|-----------|-------------|----------|-------------|----------|-------------|----------|
| Map1                   | 0.17        | 100%      | 0.35        | 100%     | 1.12        | 83.3%    | 1.05        | 87.3%    |
| Map2                   | 0.21        | 100%      | 0.46        | 100%     | 1.26        | 79.4%    | 1.77        | 80.4%    |
| Map3                   | 0.55        | 100%      | 1.56        | 100%     | 3.01        | 46.7%    | 2.91        | 48.2%    |

Tab. 1 Comparison of solution results
As shown in Fig. 7(a), although the number of IDIA and DIA variation points increased first and then decreased, the number of them was different. Specifically, the extreme value of IDIA is greater than DIA, but the total number of DIA is greater than IDIA. On the one hand, because IDIA adopts node storage structure and the single-point antibody reconstruction promotion rate in DIA is canceled, there is a lack of quantity limitation on algorithm path, which leads to the maximum variation point of IDIA is higher than DIA. On the other hand, the dynamic restriction rule results in the deletion of some variation path points with 100% confidence conditions, which is directly reflected the difference in the number of variation points in the first generation. At the same time, because the tangential undirected graph is not strictly stratified, some path nodes will be mutated in advance, resulting in the number of prophase variation path points of IDIA is more than DIA.

As shown in Fig. 7(b), the number of extension path points of DIA algorithms is always higher than IDIA, which directly results in the overall computing time of DIA being higher than IDIA. Duplication of extension path points is effectively avoided by the node storage structure, resulting in IDIA having fewer extension nodes than DIA.

5. Conclusion
The storage structure and path-point search rules of the algorithm are improved. Based on DIA, the main achievements in this paper are as follows:
1) By introducing the node storage structure, the full path is replaced by the path point, which participates in the path search as the basic unit of operation. This avoids the repeated extension calculation of path points and improves the calculation efficiency.
2) Through the path planning in the initial stage, which provides an effective reference for the subsequent mutation operation and helps the algorithm to limit the range of path point variation.
3) Layer by layer variation of the algorithm ensures the coverage of effective path points and avoids the setting of external parameters.

The algorithm path point search mechanism will be further optimized to reduce the computational cost in the next step. Meanwhile, according to the actual working conditions of mobile robots, multi-objective path planning research will be carried out to expand the application scenario of the algorithm.

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