Robot path planning based on improved sparrow algorithm

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Abstract. Robot path planning is currently a research hotspot. To overcome the shortcomings of the traditional raster method, an improved sparrow search algorithm is proposed for path planning in the raster. On the basis of the new sparrow search algorithm, the K-medoids clustering method is introduced to classify the population dynamically and accelerate the information exchange among the population. Then, an adaptive weight factor is introduced to make the algorithm search more detailed and extensive, which enhances the optimization ability of the algorithm. The optimized routes of each algorithm on the raster graph show that the improved sparrow search algorithm can plan a simpler route with the least cost.

1. Introduction

At present, human production and life are entering an intelligent stage, and many fields of robot technology have been widely used. Such as robot search and rescue, military, space search and so on. Therefore, the robot must have the ability to judge, learn and adapt. Robot path planning refers to collision-free path planning for a robot from its starting point to its end point. Nowadays, a large number of domestic and foreign scholars have done in-depth research on robot path planning and developed a variety of path planning methods. Among them, artificial potential field method, probability path method, visual method, raster method and so on are widely used.

The Raster method was proposed by W.E. Howden in 1968. It mainly establishes a route raster map based on the environment model. Environmental information is represented by a black-and-white grid. Black represents the obstacle, indicating the inaccessible area, and white represents the accessible area,
also known as the free area. The raster method uses a binary matrix for non-traversable and free areas, a matrix of 1 for obstacles, and a matrix of 0 for free rasters to create a route planning map that describes the environment.

3. Mathematical Model of Sparrow Search Algorithm

The finder is responsible for finding food for the entire sparrow population and providing direction for all followers, and finders with good fitness values will prefer food during the search process. As a result, discoverers can gain a larger range of foraging searches than followers. In each iteration, the location update formula for the discoverer is as follows:

\[
X_{ij}^{t+1} = \begin{cases} 
X_{ij}^t \cdot \exp \left( \frac{-i}{\alpha \cdot \text{iter}_{\text{max}}} \right) & \text{if } R_2 < ST \\
X_{ij}^t + Q \cdot L & \text{if } R_2 \geq ST
\end{cases}
\] (1)

In formula (1), \(t\) represents the current number of iterations, and \(\text{iter}_{\text{max}}\) is a constant representing the maximum number of iterations. \(X_{ij}\) denotes the position information of the \(i\)-th sparrow in the \(j\)-th dimension. \(\alpha \in (0, 1)\) is a random number. \(R_2 (R_2 \in [0, 1])\) and \(ST (ST \in [0.5, 1])\) represent warning and safety values, respectively. \(Q\) is a random number that follows a normal distribution. \(L\) represents a 1 x \(d\) matrix in which each element is all 1. When \(R_2 \leq ST\), this indicates that there are no predators around the feeding environment at this time, and the discoverer can perform extensive search operations. When \(R_2 \geq ST\), it means that some sparrows in the population have found predators and sent an alarm to other sparrow members in the population. At this time, all sparrows need to quickly escape to other safe places for foraging.

The location update of followers is described as follows:

\[
X_{i,j}^{t+1} = \begin{cases} 
Q \cdot \exp \left( \frac{X_{\text{worst}}^t - X_{P}^t}{i^2} \right) & \text{if } i > n/2 \\
X_{P}^{t+1} + \left| X_{i,j}^t - X_{P}^{t+1} \right| \cdot A^+ \cdot L & \text{otherwise}
\end{cases}
\] (2)

Among them, \(X_p\) is the best position occupied by the current discoverer, while \(X_{\text{worst}}\) represents the current global worst position. \(A\) represents a 1 x \(d\) matrix in which each element is randomly assigned a value of 1 or -1 and \(A^+ = A^T(AA^T)^{-1}\). When \(i > n/2\), this means that the \(i\)-th follower with lower fitness did not get food, was very hungry and needed to fly elsewhere to get more food. When the sparrow population is aware of the danger, it acts as an anti-predator, and its mathematical expression is as follows:

\[
X_{i,j}^{t+1} = \begin{cases} 
X_{\text{best}}^t + \beta \cdot \left| X_{i,j}^t - X_{\text{best}}^t \right| & \text{if } f_i > f_g \\
X_{i,j}^t + K \cdot \frac{X_{i,j}^t - X_{\text{worst}}^t}{(f_i - f_w) + \varepsilon} & \text{if } f_i = f_g
\end{cases}
\] (3)

Among them, \(X_{\text{best}}\) is the current global optimal location. As a step control parameter, \(\beta\) is a normally distributed random number with a mean of 0 and a variance of 1. \(K \in [-1, 1]\) is a random number, and \(f_i\) is the fitness value of the current sparrow individual. \(f_g\) and \(f_w\) are the current global best and worst fitness values, respectively. \(\varepsilon\) is the smallest constant intended to avoid zero in the denominator. For simplicity, when \(f_i > f_g\), this indicates that the sparrows are at the edge of the population and are extremely vulnerable to predators. When \(f_i = f_g\), this indicates that sparrows in the middle of the population are aware of the danger and need to be close to other sparrows to minimize their risk of being preyed on. \(K\) indicates the direction in which the sparrow moves, it is also a step control parameter.

4. K-medoids Clustering Algorithm

The sparrow search algorithm has good search ability, but the results of each search are random and depend on the position of the sparrow individual in the initialization population, so the stability of each search is poor. This paper uses K-medoids, a classical clustering algorithm, to perform dynamic population segmentation. Classifying sparrows into groups and classifying them at an early stage reduces the complexity of the initial work and facilitates information exchange. It then changes with
the number of iterations, increasing the diversity of the population and reducing the probability of falling into a local optimum to some extent.

The K-medoids algorithm is a widely used clustering method, which has the advantages of strong data sensitivity and robustness. The K-medoids algorithm directly selects an individual in the current cluster as the cluster center point and minimizes the distance from all other points in the cluster to this individual, thus making the cluster center point representative. The specific K-medoids clustering process is as follows:

Step1: Randomly select K individuals from the sparrow population as the initial cluster center.
Step2: Calculate the distance from other individuals to each cluster center, and divide each sparrow individual into the nearest cluster according to the principle of minimum distance.
Step3: Calculate the mean of all the individuals in each cluster, and select the individuals closest to the mean as the cluster center according to the principle of minimum distance.
Step4: Repeat Step2 until the maximum number of iterations is terminated.

5. Adaptive Dynamic Weighting Strategy

If the discoverer leads the group to search for high-quality food, it needs an accurate search mechanism. If the discoverer falls into the local optimal state, the overall search performance will be reduced. The dynamic weight factor $w$ is introduced in the discoverer stage and changes dynamically with the number of iterations, which makes the algorithm have a better search range at the beginning. The adaptive reduction of the search range in the later stage improves the search flexibility and guarantees the optimization accuracy of the algorithm to a certain extent. The discoverer’s formula for introducing the weight factor $w$ is as follows:

$$w = \frac{e^{\frac{t}{t_{\text{iter}}^\text{max}}} - e^{-\frac{t}{t_{\text{iter}}^\text{max}}}}{e^{\frac{t}{t_{\text{iter}}^\text{max}}} + e^{-\frac{t}{t_{\text{iter}}^\text{max}}}}$$

$$X_{ij}^{f+1} = \begin{cases} X_{ij}^f \cdot \exp\left(-\frac{i}{\alpha t_{\text{iter}}^\text{max}}\right) \cdot w & \text{if } R_2 < ST \\ X_{ij}^f + Q \cdot L \cdot w & \text{if } R_2 \geq ST \end{cases}$$

6. Improved Sparrow Algorithm Flow

(1) Initialization parameters. Set the population size, number of iterations and initial number of cluster centers $K$.
(2) Update the location of sparrow individuals according to the clustering algorithm $K$.
(3) Compute the fitness function to get the minimum and maximum fitness values.
(4) Select the finder from the sparrow population and update the location of the finder by formula (5).
(5) Update the follower’s position according to formula (2).
(6) Update the locations of sparrows that are aware of danger according to formula (3).
(7) To determine if the number of iterations has been reached, proceed to the next step, otherwise skip step (2).
(8) The algorithm finishes and outputs the optimal value and corresponding location.

7. Robot Path Planning Based on Improved Algorithm

To verify the feasibility and practicability of the improved algorithm, this paper takes a classic case of Robot Route Planning to explore it. Each individual sparrow is a viable path in route. Assuming there are $N$ possible paths, dimension $D$ is determined by the number of connections from the starting point to the destination point. This paper uses the raster method to model the environment. Dimension $D$ is the number of columns on the raster map. The cost function for the path length of the i-th sparrow individual is shown in equation (6).

$$f(X_i) = \sum_{j=1}^{D-1} \sqrt{(x_{j+1} - x_j)^2 + (y_{j+1} - y_j)^2}$$
In formula (6), $j$ is the j-th dimension of a sparrow individual.

8. **Experimental Simulation and Analysis**

In this paper, ISSA, SSA and PSO are used to optimize the path respectively, the total number of iterations is 50, the number of individuals in the population is 50, the learning factor of PSO is $c_1 = c_2 = 2$, $w = 0.9$, and other common parameters are consistent. The convergence diagram of route planning and cost function of each algorithm are shown in Figure 1. To avoid the contingency of the optimal route, each algorithm runs independently 10 times and counts the average value of each route, resulting in an average convergence curve as shown in Figure 2.

![Figure 1 Optimal roadmap for each algorithm](image1)

![Figure 2 Average route convergence graph for each algorithm](image2)

As shown in Figure 1-2, ISSA has a strong convergence speed, a clear and simple route with the least cost, and SSA and PSO are the most complex and costly routes to plan. From the average convergence curve, the route planned by ISSA has higher stability and the lowest cost. Therefore, the introduction of K-medoids and adaptive weighting strategy make ISSA find the best route flexibly.

9. **Concluding Remarks**

Although the traditional raster method is simple in principle and computational cost is small, it has some shortcomings in time-consuming and effect. This paper presents a mixed improved sparrow search algorithm for path planning in raster maps. K-medoids clustering method was introduced in the initialization stage to make the spatial distribution of sparrows more uniform, and adaptive weighting factor was introduced in the discoverer stage to balance the local and global searches. The experimental results show that the improved algorithm has strong optimization ability and can
effectively find a safe and least-cost route in route planning.

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