Intelligent optimization of inspection route based on multi-population integer coding particle swarm optimization algorithm

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Abstract. Aiming at the problems of premature convergence and slow convergence speed in the optimization process of single population particle swarm optimization algorithm, in order to improve the global convergence performance of particle swarm optimization algorithm, a hierarchical three-population integer coded particle swarm optimization algorithm based on grade evaluation with parallel structure is proposed and used to solve the traveling salesman problem (TSP). The algorithm imitates the form of biological aggregation in nature. In the initialization stage, three independent populations are generated according to different particle fitness, including an elite population composed of small-scale individuals with high fitness and two large-scale civilian populations composed of remaining individuals. The three populations apply the immigration strategy based on grade evaluation to exchange particles after a certain number of evolutionary generations. By applying the grade evaluation strategy, the natural law of the biological cluster is integrated into the particle swarm optimization algorithm, which effectively improves the optimization efficiency of the particle swarm optimization algorithm. The above algorithm is applied to the inspection route optimization of one of the traveling salesman problems. The results show that the improved algorithm is superior to the single population particle swarm optimization algorithm in terms of convergence speed, global optimization ability and stability.

Keywords: multi-population, particle swarm algorithm, travelling salesman problem, inspection route, intelligent optimization.

1. Introduction

Particle swarm optimization algorithm is a random search algorithm based on swarm intelligence proposed by Dr.Kennedy who is engaged in psychological research and Eberhart who is engaged in computational intelligence research in 1995. The algorithm is inspired by the regularity of bird group activity, and then a simplified model is established by using swarm intelligence[1]. The particle swarm optimization algorithm simulates the foraging behavior of birds. The search space of the problem is compared to the flight space of birds. Each bird is abstracted into a particle without volume and mass, which is used to represent a candidate solution of the problem. The process of finding the optimal solution of the problem is compared to the process of finding food. In this model, each individual in the group has the ability to control their behavior based on certain internal and external information. That is to say, each individual has a certain perception ability, which can capture the existence of the individual in the local best position around him or her and the individual in the global best position, and adjust his or her next behavior according to the current state and the information obtained, so that the whole group shows a certain intelligence. When solving optimization problems, the location of each individual can be regarded as a potential solution accordingly. According to the above rules, these potential solutions are adjusted probabilistically, and the required global optimal solution is finally obtained through repeated iterations to solve various optimization problems.

The Traveling Salesman Problem (TSP) is a well-known NP-hard combinatorial optimization problem, which is to find the shortest path problem that traverses all cities at one time and returns to the starting city. TSP has important theoretical research value and is a hot issue studied by scholars at home and abroad. It has a large number of successful applications in chip design, printed circuit board rotation, path selection, logistics distribution and other practical fields. Many modern intelligent algorithms, such as simulated annealing algorithm, particle swarm optimization, genetic algorithm, ant colony algorithm, etc. [2], can be used to solve TSP.

In the optimization process of the single population particle swarm optimization algorithm, if a particle finds a current optimal position, other particles will quickly move closer to it, and there will be ' aggregation ' phenomenon, resulting in a decrease in population diversity. If the optimal position found at present is the local optimal point, the particle swarm can not re-search in the solution space, the algorithm falls into the local optimal point, and the premature convergence phenomenon occurs. Aiming at the problems of premature convergence and slow convergence speed in the process of applying single population particle swarm optimization algorithm to solve sensor optimal placement problem, in order to improve the global convergence performance of particle swarm optimization algorithm, this paper proposes a hierarchical three-population integer coded particle swarm optimization algorithm based on grade evaluation with parallel structure. The algorithm imitates the form of biological aggregation in nature. In the initialization stage, three independent populations are generated according to different particle fitness, including an elite population composed of small-scale individuals with high fitness and two large-scale civilian populations composed of remaining individuals. The three populations apply the immigration strategy based on grade evaluation to exchange particles after a certain number of evolutionary generations. By applying the grade evaluation strategy, the natural law of the biological cluster is integrated into the particle swarm optimization algorithm, which effectively improves the optimization efficiency of the particle swarm optimization algorithm.

2. Research basis

2.1 Key steps

The key steps of the multi-population integer coding particle swarm optimization algorithm are as follows:

(1) Initialize the particles and divide them into three groups. The velocity and position information of the particles are initialized in the form of integer coding to ensure that the dimension of each particle is equal to the number of sensors to be arranged. Then the fitness value of the initial particles is evaluated, and the population is divided into a smaller elite population A and two larger civilian populations B and C based on the fitness value. Set the number of iterations Iteration = 1, the maximum number of iterations is MaxIter, and the number of iterations of the same fitness value is Samecounter = 0.

(2) Update particle velocity and position. The three populations are independent of each other, and the fitness value of each particle is calculated respectively. According to the size of the particle fitness value, the individual extreme value pbest and the global extreme value gbest of the population are determined. The particle position is updated according to Eq. (1) and Eq. (2), and the updated elite population A1 and civilian populations B1 and C1 are generated.

According to the particularity of the research object and the coding form, the update formula of the particle velocity and position can be expressed as:

$$\mathrm{v}_{\mathrm{id}}^{\mathrm{k}+1} = \mathrm{c}_1\mathrm{r}_1 \times \left(\mathrm{p}_{\mathrm{id}}^{\mathrm{k}} - \mathrm{x}_{\mathrm{id}}^{\mathrm{k}}\right) + \mathrm{c}_2\mathrm{rand}_2() \times \left(\mathrm{p}_{\mathrm{gd}}^{\mathrm{k}} - \mathrm{x}_{\mathrm{id}}^{\mathrm{k}}\right) \qquad (1)$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \quad 1 \le i \le n \quad 1 \le d \le D \qquad (2)$$

Where c_1 and c_2 are constants, and r_1 and r_2 are random numbers between (0, 1). $p_{id}^{k} - x_{id}^{k}$ denotes the set of elements in the optimal position of the particle itself that are different from the current position of the particle; $p_{gd}^k - x_{id}^k$ denotes the set of elements in the global optimal position of the particle that are different from the current position of the particle. $c_1 r_1 \times (p_{id}^k - x_{id}^k)$ indicates that the elements in $p_{id}^k - x_{id}^k$ are retained with probability. $c_1 r_1$ $c_2 r_2 \times (p_{gd}^k - x_{id}^k)$ The elements of are preserved with probability $p_{gd}^k - x_{id}^k$ $c_2 r_2$. It should be noted that in order to ensure that the number of sensors selected by all particles at any given time remains constant, i.e., the number of non-repeating elements in the particles remains constant, the different elements in p_{id}^k (p_{gd}^k) and x_{id}^k must be exchanged in pairs during each exchange.

(3) Perform mutation operations and retain better individuals. In order to enhance the global optimization ability of the algorithm and to minimize the possibility of falling into local optima, the mutation operator in the genetic algorithm is introduced in the algorithm. First, a mutation operation is performed on the particles of the elite population, i.e., a small adjustment is performed on the better particles. For example, the number of patrol points is 8. Let a particle a = [3 6 7 1 4 6 2 8 5] in the elite population, and randomly select 2 patrol points of the particles, a = [3 6 7 1 4 2 8 5], and exchange the order, then the new particle a1 = [3 1 7 6 4 2 8 5] after performing 1 mutation. Second, two mutation operations are performed on the particles of the civilian population. For example, a particle b = [28 14 6 3 5 7] in the civilian population, two sets of numbers (such as 2 and 1, 3 and 5) are randomly selected, and the exchange order is performed. The new particle b1 = [18 24 6 5 3 7] after two variations. It can be seen that the single point mutation operation only adjusts the values of the two dimensions of the particles, and the better particles can be adjusted in a small range to achieve the effect of local optimization. The multi-point mutation operation adjusts the four dimensions of the particles, which can make a large adjustment to the particles with poor fitness, and accelerate the generation of particles with higher fitness. The mutation operator provides a method to generate new solutions, so that the generation of new solutions is not affected by other particles, and the diversity of the population is improved. The fitness values of each particle before and after the mutation operation are compared, and the particles with higher fitness are retained to generate a new elite population A2 and civilian populations B2 and C2.

(4) Determine whether the immigration conditions are met to complete the exchange of individuals in the elite population and the civilian population. For example, set the immigration frequency f=2, the number of immigrants T=2, are set, i.e., an immigration operation is performed every two iterations. The two particles with the largest fitness in each civilian population enter the elite population, corresponding to the four particles with the lowest fitness in the exchange elite population. Through the migration operation based on grade evaluation, the high-quality individuals obtained in the optimization process can be selected, and the exchanged particles can be used as ' exotic species ' to improve the diversity of the population and avoid the algorithm falling into local optimum.

(5) Determine whether the termination condition is satisfied. By comparing the global optimal fitness values before and after the iteration update, the Samecounter increases by 1 when it is equal, and the fitness value is updated and Samecounter is cleared when it is not equal. When Samecounter or Iteration reaches the set value, the iteration is terminated and the final result is output. If not satisfied, turn to step 2.

2.2 Selection of fitness function

In the discrete PSO algorithm, the corresponding fitness function (i.e., the total path length of TSP) is defined as

$$f(X_i) = \sum_{k=1}^{N-1} d_{ik(k+1)} + d_{1n} \tag{3}$$

The particle position with the smallest fitness value of the function is the optimal solution of TSP.

3. Intelligent optimization of inspection route

There are many on-site inspection equipment and more inspection items in enterprises, and minor negligence may lead to major mistakes. The inspection personnel automatically obtain the requirements of the inspection task through the mobile terminal, complete the data collection according to the specified time, specified location and specified requirements, and transmit the information of the operation status of the equipment and facilities, the failure of the equipment and facilities, and various hidden dangers of safety production back to the management background in real time, so as to realize the sharing of inspection data among the operators, managers and various information systems of the enterprise, and comprehensively and systematically grasp the operation status of the equipment and facilities and the safety status of the personnel[4-5].

In view of the random setting of the inspection route and the low efficiency of the inspection in the enterprise inspection, the inspection route is optimized based on the swarm intelligence algorithm, and the inspection route is automatically intelligently sorted, and the optimal inspection route is calculated, so as to derive the scientific inspection route.

4. Algorithm optimization results

Taking the inspection route of an enterprise as an example, the number of inspection points is 31. The discrete particle swarm optimization algorithm (DPSO algorithm), the double structure coding genetic algorithm (GA) and the algorithm proposed in this paper are used to optimize 100 times respectively. The optimization results are shown in table 1.

Table 1.Comparison of the search performance of the 3 algorithms

Number of inspection points	Algorithm	Known total length of shortest path (m)	Probability of getting the optimal value (%)	Mean value (m)	Average number of iteration steps
31	DPSO	15601.9195	90	15610.6234	153
	GA		89	15615.7695	149
	Algorithm of this paper		99	15602.6458	134

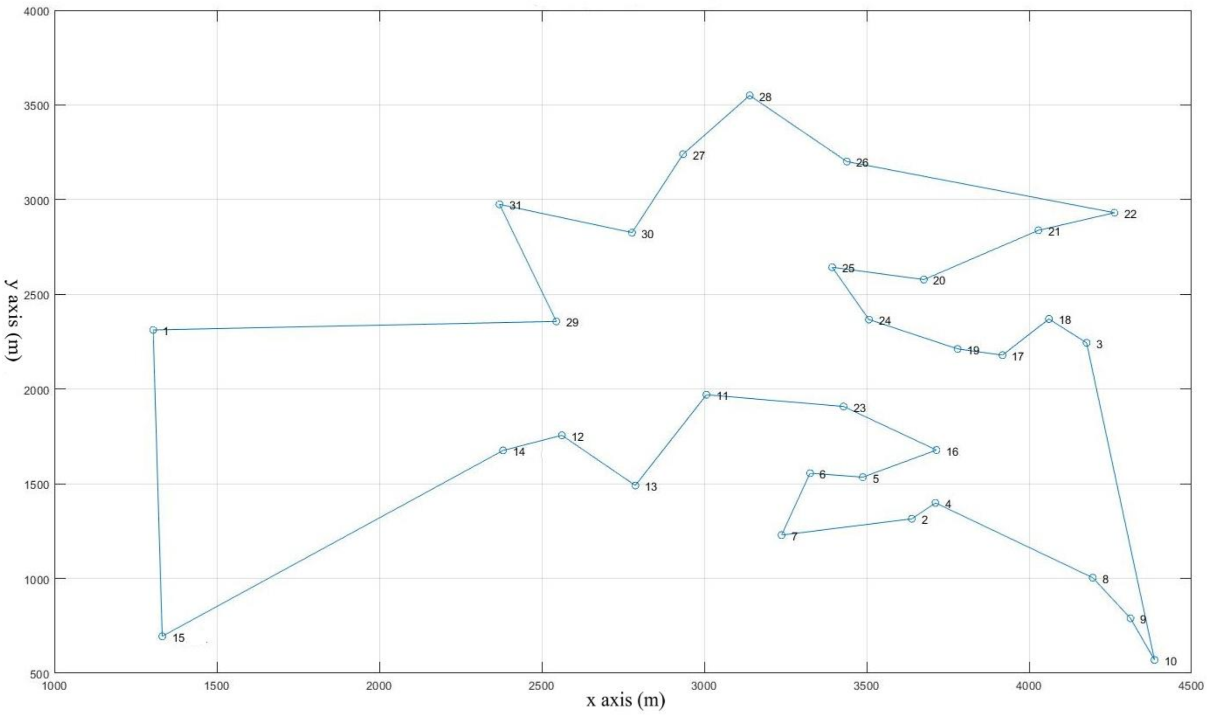

Fig. 1 Optimization path

5. Conclusion

Aiming at the problems of slow convergence speed and easy to fall into local optimum in single population particle swarm optimization algorithm, this paper improves the discrete particle swarm optimization algorithm and proposes a hierarchical three-population integer coded particle swarm optimization algorithm based on hierarchical evaluation. By applying the grade evaluation strategy, the natural law of the biological cluster is integrated into the particle swarm optimization algorithm, which effectively improves the optimization efficiency of the particle swarm optimization algorithm. The improved algorithm is applied to the field of intelligent optimization of inspection route, and good results are achieved.

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