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Abstract. The TSP is a typical NP problem. The optimization of vehicle routing problem (VRP) and city pipeline optimization can use TSP to solve; therefore it is very important to the optimization for solving TSP problem. The genetic algorithm (GA) is one of ideal methods in solving it. The standard genetic algorithm has some limitations. Improving the selection operator of genetic algorithm, and importing elite retention strategy can ensure the select operation of quality, In mutation operation, using the adaptive algorithm selection can improve the quality of search results and variation, after the chromosome evolved one-way evolution reverse operation is added which can make the offspring inherit gene of parental quality improvement opportunities, and improve the ability of searching the optimal solution algorithm.

Key words: genetic algorithm; improvement; encode; selection; crossover; mutation.

INTRODUCTION

The traveling salesman problem, namely TSP (Traveling Salesman Problem) also translated into traveling salesman problem, which is one of the most famous problems in mathematics. Suppose that a traveling salesman wants to visit n cities. He must choose the way to go. The limitation of the path is that every city can only visit once, and finally return to the original city. The choice of the path is that the required path is the minimum of all paths. The earliest mathematical programming of the traveling salesman problem was proposed by Danzig (1959), and it was studied in the field of optimization. Many of the optimizations are used as a benchmark for testing. Although the problem is computationally difficult, many heuristic algorithms and precise methods have been used to solve tens of thousands of instances, and the error can be controlled within 1%.

THE DESCRIPTION OF THE TSP PROBLEM

TSP can be described as: in a complete graph with n node, find a shortest Hamiltonian loop that traverses all nodes and each node is only accessed 1 times. That is a full array of $P(X)=\{V_1,V_2,V_3,...,V_n\}$ of the natural subset $X=\{1,2,3,...,n\}$ (The number of the elements in the X set corresponds to the number of the n cities) is searched, and the target function $T_d=\sum_{i=1}^{n-1}D(V_i,V_{i+1})+D(V_n,V_1)$ is minimization. Among them, $D(V_i,V_{i+1})$ represents the distance between the city V_i and the city V_{i+1}.

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STANDARD GENETIC ALGORITHM

Genetic algorithm is a kind of randomization search method, which is evolved from the evolutionary laws of the biosphere (Survival of the fittest, survival of the fittest). It was first proposed by Professor Holland in the United States in 1975. The genetic algorithm uses the value of the individual fitness function in the population as the search information, and the search range is all the individuals of the population.

The basic operation process of the genetic algorithm is as follows:

1) Initialization: set the evolutionary algebra counter $t = 0$, set the maximum evolutionary algebra T, and randomly generate M individual as the initial group $P(0)$.

2) Individual evaluation: The fitness of each individual in the group $P(T)$ is calculated.

3) Selection operation: the selection operator acts on the group. The purpose of the selection is to inherit the optimized individuals directly to the next generation or to produce new individuals by pairing and cross operating to the next generation. The selection operation is based on the fitness evaluation of the individual in the group.

4) Cross operation: the crossover operator is acted on the group. The key role of genetic algorithms is the crossover operator.

5) Mutation operation: the mutation operator is used in the group. It is a change in the value of certain genes of individuals in a group.

6) The group $P(T)$ gets the next generation group $P(T+1)$ after the selection, crossover and mutation operation.

7) The termination condition judgment: if t=T, the maximum fitness individual obtained in the evolutionary process is used as the optimal solution, and the calculation is terminated.

IMPROVED GENETIC ALGORITHM

Encode

In the TSP optimization problem, there are n cities, assuming that the number of each city is an integer 1,2,3,...,n. and such a chromosome is made up of a n segment. For example, there are 10 cities in the TSP problem, then {1, 3, 4, 2, 6, 9, 10, 8, 5, 7} is a legitimate chromosome and a possible optimal solution.

Initialization Population

A random function is used to generate an initialization population. The size of the initialization population is related to the number of cities in the TSP problem. Generate the initialization population $A(0) = \{X_1^0, X_2^0, X_3^0, ..., X_n^0\}$ randomly according to a certain rule.

Fitness Function

Whether the individual evolution of a population is a better solution to the problem, that is, to see its adaptability, the standard of evaluation is the value of the fitness function. The value of fitness function is the only basis for the survival of the fittest in the process of population evolution. The value of individual fitness function is larger, which indicates that the individual is more competitive in survival and is more likely to be chosen to evolve. Otherwise, the smaller the value of the individual fitness function, the weaker the individual survivability, the higher the possibility of being eliminated in the evolution of the group. The fitness function of the individual in this paper is:

$$F(R_i) = 1/[\sum_{i=1}^{n-1} D(V_i, V_{i+1}) + D(V_n, V_1)] \tag{1}$$

The $D(V_i, V_{i+1})$ in the form indicates the distance between the city V_i to the city V_{i+1}, and the R_i represents the path i.

Selection Operation

The selection operation is to generate a new population with higher values of the fitness function from the current population by a certain selection probability. Its main purpose is to inherit the high quality genes to the next generation, and to improve the efficiency of calculation and the probability of global convergence. The calculation method of individual selection probability in this paper is as follows:

$$p_i = F(q_i) / \sum_{i=1}^{n} F(q_i) \tag{2}$$

$F(q_i)$ Is the value of the fitness function of the individual q_i. In this paper, an elite reservation strategy is added to the selection operation, that is, an elite individual with the maximum value of the fitness function is added to each generation. The individuals of population have undergone mutation and cross evolution. If the best individual in the new generation of population is better than the elite individual, the elite individual will be replaced by the best individual, otherwise the elite individual will be retained. This elitism selection strategy ensures that the best individual in the parent population will not be lost due to variation or crossover. The best individual in the offspring population are better than the best individual in the parent population.

Crossover Operation

Crossover is a very important operator, and the purpose is to cross the selected high-quality individuals to get better new individuals. The range of cross probability is generally recommended as 0.4-0.99.

In this paper, an elite individual and a selected new individual are partially mapped and hybridized, and the location of the cross is randomly generated. It is assumed that the number of cities is 10, and the cross operation algorithm is as follows:

1) select the best individual of the parent population and a new individual;

2) 2 crossover locations a and B are generated randomly, $n_1, n_2 \in [1,10]$, cross operation of the data between the 2 positions.

3) If the new individual city number is repeated after crossing, the partial mapping method is used to eliminate repetition and non-repetition number reservation.

This cross method can ensure that the high quality gene patterns in parent offspring can be well protected, so that high-quality chromosomes can be inherited to the next generation, which is conducive to improving the performance of genetic algorithm.

Mutation Operation

Mutation operation is one of the important operations of the genetic algorithm. A new individual is formed by changing the encoding of some bits in the coded string with the other bit codes in the string. The mutation operation determines the local search ability of the genetic algorithm, maintains the diversity of the population, and avoids the appearance of the precocious phenomenon. In order to ensure the stability of population evolution, the mutation probability generally takes smaller values. This paper uses an adaptive mutation probability, as shown below:

$$P_m = \begin{cases} P_{m-\max}(P_{m-\max} - P_{m-\min})(F - F_{avg}) / (F_{\max} - F_{avg}), F \geq F_{avg} \\ P_{m-\max}, F < F_{avg} \end{cases} \tag{3}$$

Among them, $P_{m-\max}$ is the maximum mutation probability and 0.05 is taken in this paper. $p_{m-\min}$ Is the minimum mutation probability, and 0.01 is taken in this paper. F Was the adaptability of the mutant individuals, and $F_{\max}$ was the largest fitness value in the population, and F_{avg} was the average fitness value of the current population.

Evolutionary Reversal Operation

Evolutionary reversal operation can improve the local search ability of genetic algorithms. This paper introduces evolutionary reversal operation after selection, cross and mutation operation. The reverse algorithm is as follows: first generate 2 random integers n_1 and n_2 randomly $n_1, n_2 \in [1,10]$ to determine 2 positions, and then change the position of the two cities in the TSP solution. If a=2, b=5, the previous tour route is $\{ V_1, V_2, V_5, V_{10}, V_8, V_6, V_3, V_7, V_4, V_9 \}$, after the reverse operation, the tour route is $\{ V_1, V_5, V_2, V_{10}, V_8, V_6, V_3, V_7, V_4, V_9 \}$.

SIMULATION EXPERIMENTS AND RESULTS

In this paper, ten cities and thirty cities are tested separately.

1) The city coordinates of ten cities are as follows:

(0.4 0.4439), (0.2439 0.1463), (0.1707 0.2293),
(0.2293 0.761), (0.5171 0.9414), (0.8732 0.6536),
(0.6878 0.5219), (0.8488 0.3609), (0.6683 0.2536), (0.6195 0.2634).

2) The city coordinates of thirty cities are as follows:

(41 94), (37 84), (54 67), (25 62), (7 64), (2 99), (68 58), (71 44), (54 62), (83 69), (64 60), (18 54), (22 60), (83 46), (91 38), (25 38), (24 42), (58 69), (71 71), (74 78), (87 76), (18 40), (13 40), (82 7), (62 32), (58 35), (45 21), (41 26), (44 35), (4 50).

The TSP problem is solved by using the standard genetic algorithm and the improved algorithm in this paper. The two algorithms have the same basic parameters and repeat each time 20 times. The simulation results are shown in Figure 1, Figure 2, Figure 3 and Figure 4 below.

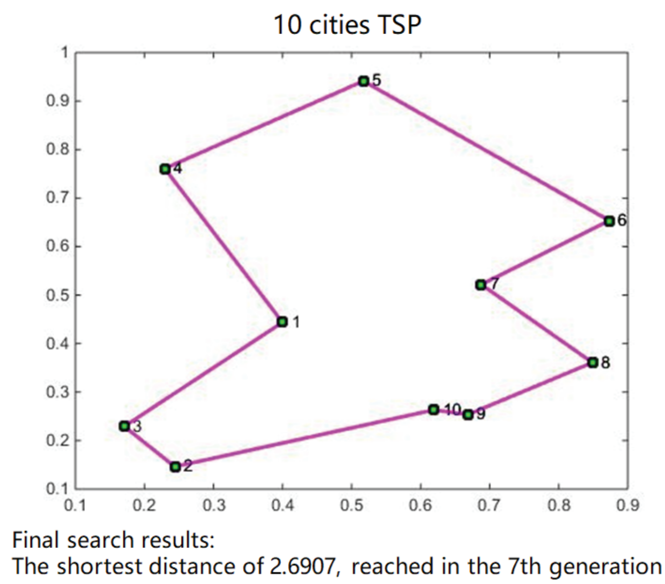

FIGURE.1 results of improved genetic algorithm for ten cities

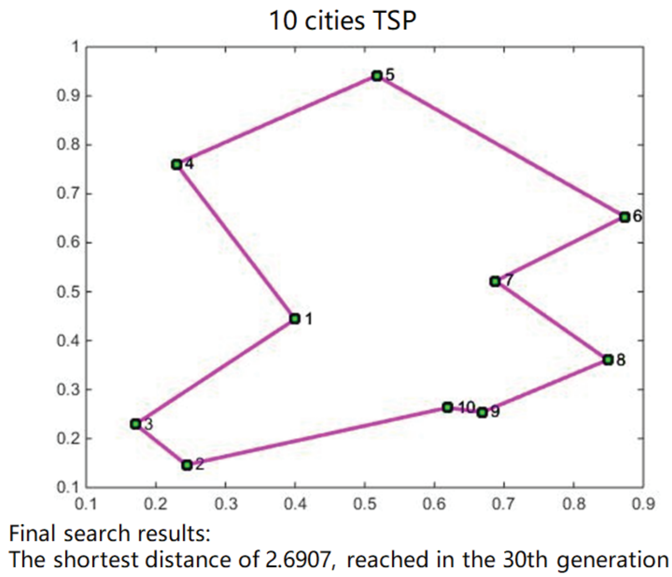

FIGURE.2 Results of standard genetic algorithm for ten cities

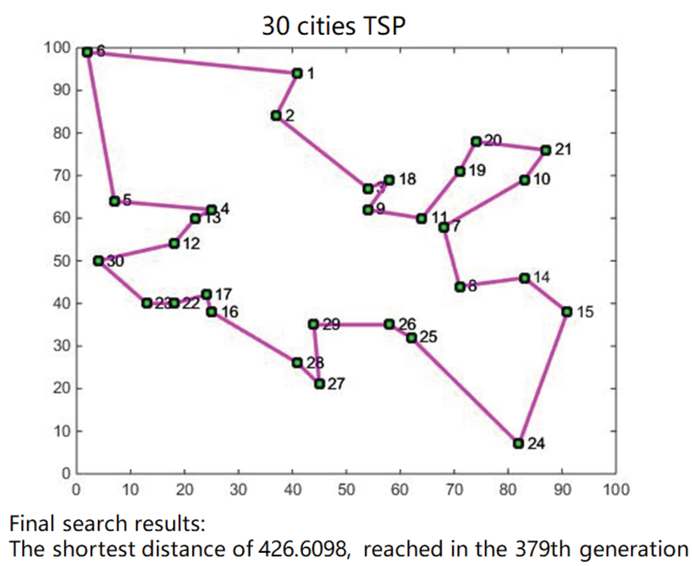

FIGURE.3 Results of improved genetic algorithm for thirty cities

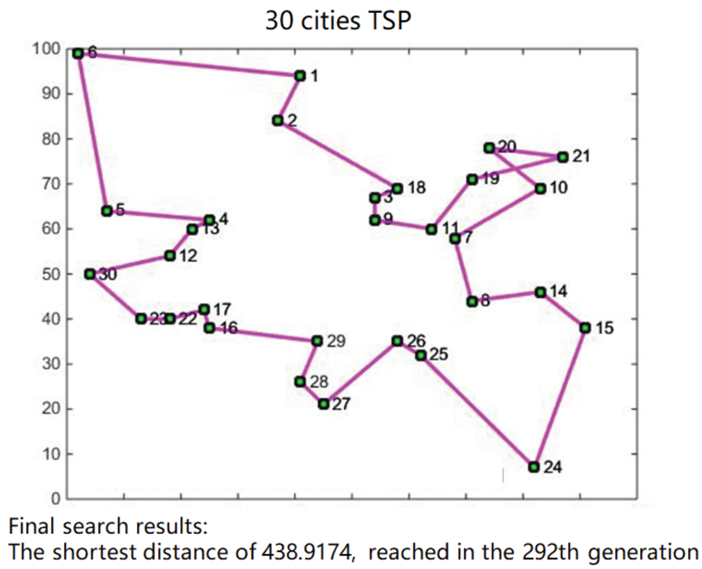

FIGURE.4 Results of standard genetic algorithm for thirty cities

From Figure 1 and Figure 2, we can see that under the same experimental conditions, the standard genetic algorithm needs 30 iterations to get the optimal solution. The improved genetic algorithm achieves the best solution in seventh iterations. It can be seen that the improved genetic algorithm has higher operational efficiency. From Figure 3 and Figure 4, we can see that when the number of cities is large, under the same experimental conditions, the improved genetic algorithm can get the optimal solution, while the standard genetic algorithm is trapped in the local optimal solution. It can be seen that the improved genetic algorithm is easier to jump out of the local optimal solution.

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