AN IMPROVED SIMULATED ANNEALING ANDGENETIC ALGORITHM FOR TSP

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Abstract: In order to improve the evolution efficiency and species diversity of traditional genetic algorithm in solving TSP problems, a modified hybrid simulated annealing genetic algorithm is proposed. This algorithm adopts the elite selection operator to ensure not only the diversity of the algorithm but also that groups are always close to the optimal solution; at the same time, places the simulated annealing algorithm in the evolutionary process of genetic algorithm, and using the hybrid algorithm dual criteria to control algorithm's optimize performance and efficiency simultaneously. The final example shows that the hybrid algorithm is an optimization method with higher optimize performance, efficiency and reliability.

Keywords: TSP; Elite selection operator; Genetic Algorithm; Simulated annealing algorithm

1 Introduction

The TSP (Traveling Salesman Problem), which was proposed by K. Menge, has aroused interest of many researchers in various fields since 1932. TSP problem is a combinatorial optimization problem with widely applied background and important theoretical value, namely that for a given set of n cities and direct distance between any two to find out a closed shortest path that travels every city once and only once, TSP has proved that belongs to a typical NP-hard problem and has not yet been completely resolved [1-3]. At present, the more effective intelligent optimization algorithms for TSP mainly include the Genetic Algorithm (GA), Simulated Annealing Algorithm (SA), Tabu Search Algorithm (TS) and neural network algorithm, etc.

GA is an adaptive global optimization probability search algorithm with strong global search ability, but it is prone to premature convergence of the algorithm in practical applications because of its poor local search ability. The more difficult problem in GA is how to choose the selection method that can make the best individual preserved as well as maintain the diversity of population [4]. SA has strong local optimization ability, also can overcome the dependence of the initial value and the local minimum in the optimization process, but due to the lack of the understanding lack of the whole search space condition, the search process is therefore not conducive to enter the most promising search area, resulting in operation inefficiency in global search algorithm [1, 3]. Currently, there have been a lot of studies that take advantage of GA, SA and the hybrid algorithm for TSP issues. It combines gene pool (Ge) and GA so as to direct the evolution of the whole population in Ref. [5]; Ref. [6] proposed elite adaptive hybrid genetic algorithm; The Ref.[7] designed a "Disaster Operator" as a new selection operator to improve the convergence speed.

All the above methods play an important but not completely efficacious role in improving the convergence speed and diversity of the population, so this paper proposes an improved Hybrid Simulated Annealing Genetic Algorithm (HSAGA) that puts SA into the evolutionary process of modified Simple Genetic Algorithm (SGA). Then it also verifies that the hybrid algorithm is an optimization method with higher optimization performance, efficiency and reliability by comparing with SGA and GA that proposed in Ref. [8].

2 TSP

With graph theory language, TSP can be described as follows: Given an undirected weighted graph $G=(V,E)$, let $V=\{1,2,\cdots,n\}$, E and $d_{ij}(i,j=1,2,\cdots,n)$ be the vertex set, the edge set composed of the interconnected vertices and the weight of edges (i,j), then the cost of a loop is the sum of the weights of all edges[2]. TSP is asked to identify a line of least cost, which is the shortest Hamilton circuit that traverses the entire vertices if besides the same initial and final vertex. Learn from Ref. [2], TSP mathematical model can be established as follows:

$$\min F = \sum_{i \neq j} d_{ij} x_{ij}$$

$$x_{ij} = \begin{cases} 1, \ edge(i,j) \ \text{in the optimal path} \\ 0, \ \text{otherwise} \end{cases} \tag{1}$$

$$\sum_{i \neq j} x_{ij} = 1 \ ; \qquad i \ j \in V \tag{2}$$

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$$\sum_{i,j \in V} x_{ij} \le |S| - 1; \qquad S \subseteq V \tag{3}$$

where, $|S|$ means the number of vertices that contains of G in set S. Eq. (1) gives a definition of x_{ij}, Eq. (2) shows that each vertex can be accessed once, Eq. (3) guarantees that no subloop will be engendered.

2.1 City representation

In this study, put the cities on the XOY coordinate plane, the specific location of each city was shown by a two-dimensional coordinates.

2.2 Distance between cities

The direct distance between the two adjacent cities, namely the right $d_{ij}(i, j = 1, 2, \cdots, n)$ of (i, j) was represented by the Euclidean distance. For example, the distance between the city $i(x, y)$ and $j(x', y')$ is defined as:

$$d_{ij} = \sqrt{(x - x')^2 + (y - y')^2}$$

3 Algorithm design

Based on the research of basic GA species diversity and the premature convergence problem，the core of this improved algorithm is: use the elite selection operator instead of the traditional selection operator to ensures the diversity of population; at the same time, select the "elite" into the genetic group can pledge that the sub-generation performance is not worse than their parents', so that the community is always close to the optimal solution. In the later evolutionary of GA, because that its weak ability of local optimization can lead to a slower convergence speed, the algorithm is easy to fall into local optimum, the simulated annealing algorithm accept the new state by Metropolis sampling stability criterion, that means when the initial temperature is sufficiently high, the cooling is slow enough, the sampling for each temperature is long enough and the final temperature tends to 0, The algorithm converges to the global optimal solution with probability 1 eventually [1]. Therefore, do the annealing operation in the later genetic evolution, regard the evolution result of genetic operation as the annealing process initial population, and the annealing temperature is used to control algorithm solving process optimization toward the minimum, accept the optimal solution at the same time to accept inferior solution in a certain probability, then take back the obtained solution by Metropolis sampling and annealing operation as the initial population of GA for genetic operation, Thereby effectively avoid the local optimal solution and finally tends to the global optimal. The process of improved HSAGA Optimization for TSP is shown in Figure 1.

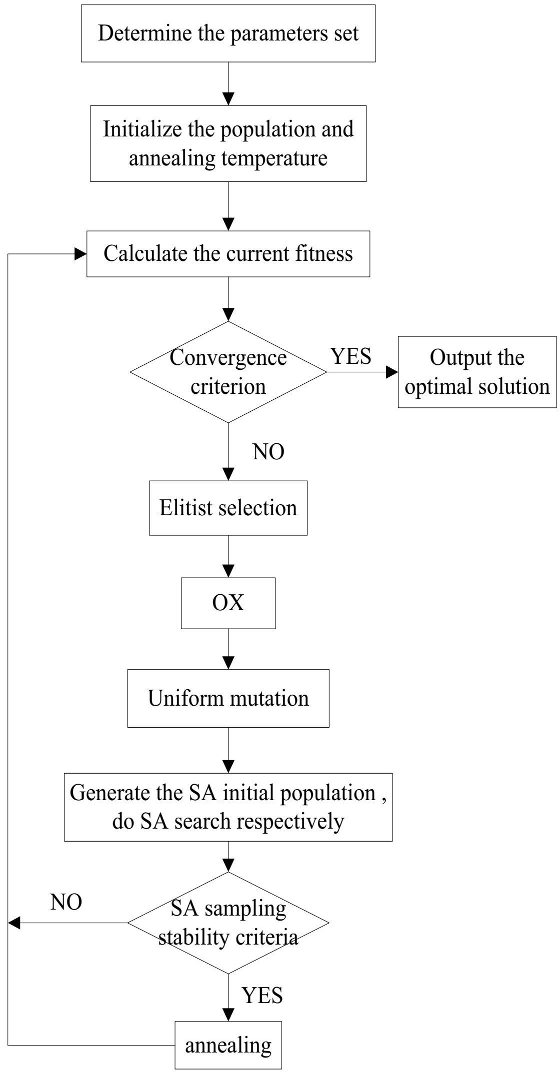

Figure 1 The hybrid optimization flow of improved GASA for TSP

3.1 Coding

The common TSP coding strategies are mainly binary coding and path coding. Binary code affects the efficiency of the algorithm and requires additional correction operator to ensure the legitimacy of the solution [1], so it is not conducive to the hybrid algorithm realization. Just because of this, this paper adopts path coding which means constructing the optimization state directly by using the location of the city in the path, for example, the corresponding path coding of 4-2-7-9-5-1-6-3-8 is（4 2 7 9 5 1 6 3 8). This encoding form, which is naturally intuitive, helps to design of optimize the operation.

3.2 Fitness function

Fitness is used to assess the merits and adaptability of the individuals in GA. TSP is minimizing objective function, so its fitness function will be designed as: $f = 1/F$.

3.3 Selection

SGA usually uses proportional selection operator, which means the probability that the individual is selected and inherited to the next generation is in direct proportion to its fitness. Although this operator has a relatively high selectivity for the individuals with high fitness, it does not necessarily choose the most outstanding individuals and inherit them into the next generation to guarantee the performance of progeny populations are always better than the parents', at the same time, crossover and mutation operation may damage the outstanding individuals' genes in the parents, Therefore, the evolutions of group will be reduplicate and even temporarily retrogressive what may slow down the convergence speed. Based on this, we could use the elite selection operator to overcome the deficiencies of the selection operation in SGA.

Elite selection operator[6] refers to that choose the best two individuals into the next generation populations from each of the "family" which is formed by randomly paired separately parent individuals after crossover and mutation and the formation of offspring.

Elite selection operator makes a pair of parents' genetic out several children (the number of children can be set), ensures the diversity of population; then select the "elite" into the genetic group can pledge that the sub-generation performance is not worse than their parents', so that the community is always close to the optimal solution. The specific steps are:

Step 1: Pair off randomly the individuals in the t generation population;

Step 2: Each individual do the crossover and mutation respectively for N times to produce a total of $2N$ offspring individuals;

Step 3: Each pair of parents individuals and their own resulting offspring form a "family" with $(2+2N)$ individuals, then pick out two individual of best fitness to form the $t+1$ generation population.

3.4 Crossover and mutation

Crossover operation is an important means of GA to acquire new excellent individuals, mutation makes the GA to maintain the population diversity and overcome its premature convergence to some extent. This paper put Ordered Crossover (OX) [7] and uniform mutation to use.

3.5 SA process

SA starts with a higher initial temperature; then searches randomly in the solution space by Metropolis sampling strategy with probabilistic jumping characteristics; thirdly, repeats sampling process as the temperatures falling; later, in an interview with high-quality solution accepts the inferior solution temperately at the same time, thus effectively escapes from the local optimal solution, finally gets the global optimal solution; following are the specific steps:

Step 1: Given the initial temperature T_0 and state i ;

Step 2: Generate a new state j from i through the state generation functions, and then calculate the delta function $\Delta f = f(j) - f(i)$;

Step 3: If $\Delta f \le 0$, accept the new state, then copy it into the next generation population;

Step 4: If $\Delta f > 0$, generate acceptance probability $p = \exp(-\Delta f / T)$ (where, $T = k * T_0$, k is the coefficient of temperature drop, in addition set the termination temperature for T_f) and uniformly distributed random number $random$ in [0,1], if $random < p$, accept the new state j , then copy it into the next generation population; otherwise, discard j , copy the primary i .

3.6 Algorithm termination condition

The proposed hybrid algorithm take genetic algorithm as the outer loop, and simulated annealing algorithm as the inner loop to avoid the outer GA catch into local optimum by taking advantage of the strong local search ability of simulated annealing. In the algorithm design process, this paper takes advantage of the dual criteria of GASA Hybrid Algorithm. The outer convergence criteria can be used to determine the trends and ultimate state of the algorithm optimize the performance; The inner sampling stability criteria can be used to decide the number of candidate solutions generated at each temperature and the algorithm's search capability and performance, also it's the switch condition from SA to the GA in hybrid algorithm.

4 Simulation

In order to confirm the hybrid algorithm efficiency, the paper solves the TSP with 10 cities by using the SA, GA that proposed in Ref. [8] and the algorithm in this paper respectively.

The experiment parameters are set to: population size 100, crossover and mutation probability for 0.7 and 0.1, maximum evolution generation is 200, each pair of parents produces 100 son generations; in SA, the initial temperature 10000, cooling coefficient and final temperature of 0.95 and 0.1. The result comparisons of algorithm that presented in Ref. [8] and this paper as follows in Table I.

In Ref. [8], it's verified that in solving TSP, GA could gain better result and search faster than SA, therefore, compare the optimal path determined by GA and HSAGA as shown below in Figure 2.

Table I Comparison of experimental results

	Comparison of Experimental results		
	Number of runs	**Optimal solution**	**Frequency to get optimum（%）**
SA in Ref.[8]	20	4.3268	5
GA in Ref.[8]	20	3.7659	10
HSAGA	20	3.2732	95

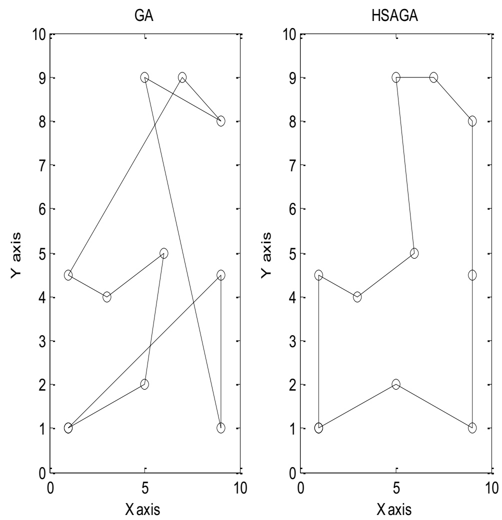

Figure 2 The optimal path taken by GA and this HGASA

The results in solving TSP problem shows that compared with the GA and SA in the Ref. [8], the proposed HSAGA can get a shorter overall length path and a higher frequency to achieve the optimal solution under the same number of runs; In the Figure 2, the optimal path obtained by GA can be overlapping and cross since that GA may be trapped into local optimum in the evolutionary process, but the hybrid algorithm improved this defect of GA by using the SA's strong ability of local search in the later evolutionary so that to get a more satisfactory result.

From the overall, the proposed HSAGA is with high evolutionary efficiency and strong optimal solution search ability.

5 Conclusions

1) Improve the SGA, make use of the elite selection operator to ensure the algorithm diversity, and overcome the algorithm "premature" convergence to some extent;

2) Combine the strong local search ability of SA with the global optimization capability of GA, enhance advantage and avoid disadvantage, put SA into the evolutionary process of GA to improve the evolutionary efficiency of the algorithm;

3) In solving TSP, the HSAGA in this paper has superiority in evolutionary efficiency and maintaining diversity of the population.

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