Multi-parent Dynamic Nonlinear Crossover Operator for TSP

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Summary
This paper proposed a new multi-parent dynamic nonlinear crossover operator, which is using the local information effectively and being little relation with the first city, and a new dynamic parent selection principle is designed. Experiments on TSPLIB is made to show that the new crossover operator is useful and simple.

Key words:
Genetic Algorithm; Traveling Salesman Problem; Multi-parent Dynamic Nonlinear Crossover Operator

1. Introduction

The traveling salesman problem (TSP) is well known to be NP-complete. It is mostly studied in the form of an optimization problem where the goal is to find the shortest Hamiltonian cycle in a given weighted graph. Here we will restrict ourselves to the symmetric traveling salesman problem, i.e., distance(x,y)=distance(y,x), with Euclidean distances in a two-dimensional space.

Over time, much study has been devoted to the development of better TSP solvers. Where "better" refers to algorithms being more efficient, more accurate, or both. It seems, while this development has in progress, most of the effort went into the construction of the algorithm, as opposed to studying the properties of traveling salesman problems.

Several approximation techniques including the classical local search algorithms [1], genetic algorithm (GA) [2], ant colony optimization [3] and etc. has been proposed in the literature. Although some of these approaches have proven to be successful in producing quite good results, they are still far away from the perfect solver of TSP.

Many researchers focus on the chromosome representation and the genetic operator. The representations proposed including ordinal representation, binary representation, and path representation; while the crossover operators proposed including heuristic crossover, cycle crossover, order crossover, 2-exchange crossover heuristic crossover [4] and etc. Unfortunately, all these created offspring seemed does not inherit enough adequate information form its parents.

Multi-parent recombination [5][6] is an attention-getting research area of GA in recent years. Multi-parent recombination operators do improve the performance of GA, on the country; the performance of multi-parent recombination is sensitive to the parent number. Therefore, it is necessary for us to find a more broad-spectrum and robust solution to improve the performance of GA.

To overcome this disadvantage, a multi-parent dynamic nonlinear crossover operator, which uses multi-parent strategy, is proposed. This operator utilizes many parents information and provides a large number of materials exchange.

The paper is organized as follows. Section 2 provides a briefly description about the traveling salesman problem. The new multi-parent dynamic nonlinear crossover operator is described in Section 3. In Section4, we compare our results with2-exchange crossover heuristic crossover for TSP problem instances.

2.Traveling Salesman Problem

When a busy salesman is to travel cities, starting from and returning to his hometown, it is in his own interest to plan the tour so the total distance he has to travel will be minimized. If he knows the distance between each pair of cities, how can he construct a sequence of the cities, so that the total distance he has to travel is minimized?

Although the number of salesman around the world desiring for an algorithm to solve this problem may not be enormous and the number of obvious practical applications is limited, the traveling salesman problem is a frequent subproblem of other complex applications and one of the most researched problems in scientific literature. A general definition of the traveling salesman problem is:

Given a set V of n cities $c_1, c_2, \ldots, c_n$ and a distance d_{ij} between each pair of cities (c_i , c_j),we wish to find a permutation π of the cities, so that the total distance of the resulting tour is minimized.

It means

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

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$$s.t.\ \sum_{j \neq i} x_{ij} = 1$$
$$\sum_{i \neq j} x_{ij} = 1$$
$$\sum_{i,j \in S} x_{ij} \leq |S| - 1$$
$$x_{ij} \in \{0,1\}$$

where $x_{ij} = \begin{cases} 1, (i, j) \in \pi \\ 0, otherwise \end{cases}$,S is an arbitrary subset of C, |S| means the element numbers.

3. Multi-parent Dynamic Nonlinear Crossover Operator

Though multi-parent crossover operators own many more chances to escape from a local optima, the number of parent is selected difficulty and dependent with different problems. In this paper, multi-parent dynamic nonlinear crossover operator uses a dynamic parents selection principle, in which each individual vector is replaced by each offspring vector, where some offspring vectors are computed with full information of parents vectors located in the same group, while the others are selected randomly.

3.1 Dynamic Parents Selection

Suppose $X(t) = (x_1, x_2, ..., x_N)$ is the population at time t, where x_k represents the k-th chromosome, and N is the number of chromosomes. $f(X) = (f(x_1), f(x_2), ..., f(x_N))$ is the fitness vector of the population at time t, where $f(x_k)$ represents the fitness value of k-th chromosome. To use dynamic parents selection, we can determine the groups though the number of groups and parent number in each group are not known. From the obtained results of test experiments, using more parents makes it harder for a super chromosome to deliver its identical copies in the next generation, this implies a more diverse search with a reduced danger of premature convergence. From this point, group should own a large number of chromosomes. In contrast, more parent number decreases the computational efficiency also. To balance the diversity and computational efficiency, the parent number within each group is stochastic established, though it is limited by

$$2 \leq Group\_Number_j \leq \frac{N}{2}$$

where $Group\_Number_j$ means the number of parent individuals within group j. Thus the group is established.

3.2 Multi-parent Dynamic Nonlinear Crossover Operator

Suppose group i contains k parent vectors, for convenience, $Group_i = (x_1, x_2, ..., x_k)$, where $x_j = (x_j^1, x_j^2, ..., x_j^m)$, $j = 1,2,...,k$, and x_j^s means the s-th variable of parent vector x_j, thus k offspring vectors is needed. Multi-parent dynamic nonlinear crossover operator only produces two offspring vectors using their own information, and the others are created randomly. Thus the diversity of population is guaranteed. So, in the following part, we only discuss offspring vector $w = (w_1, w_2, ..., w_n)$ and $v = (v_1, v_2, ..., v_n)$.

First of all, we will consider how to produce offspring vector $w = (w_1, w_2, ..., w_n)$. Suppose $w_1 = x_1^1$, and make the first city of other k-1 parent vector is the same (change the first city, if not same). Random select length $t(\leq \frac{n}{2})$, suppose $\sum_{j=1}^{t-1} d(y^j, y^j) = \min_s \sum_{j=1}^{t-1} d(x_s^j, x_s^{j+1})$, we have

$$w_1 = y^1, w_2 = y^2, ..., w_{t-1} = y^{t-1}$$

and the k parent vectors is updated with

$$x_j = (w_1, w_2, ..., w_{t-1}, x_j^t, ..., x_j^m)$$

where $x_j^t, ..., x_j^m$ are the m-t variables of parent vector x_j, and the order is the same with the original order. Continue the process until all the variables is determined.

The second offspring vector $v = (v_1, v_2, ..., v_n)$ can be produced with the above mentioned algorithm, though the first city v_1 of v is the last city of w. In this manner, we will give a new algorithm to produce offspring vectors. It increases the materials utilizing and provides a broaden diversity measure.

3.3 Structure of Multi-parent Dynamic Nonlinear Genetic Algorithm

The nonlinear genetic algorithm can be sketched as follows:

```
Main()
{
```

Choose an initiate population P(0), determine the coefficients: K and Pm;

Do

{

Dynamic Parent Selection;

Multi-parent Dynamic Nonlinear Crossover Operator;

Elitism to preserve the best individual;

}while (some stopping criterion applies);

Output the final best solution;

}

4.Simulation Results

A number of TSP problem instances have been selected with which to test our scheme. These problem are from TSPLIB[7]. To testify the advantages of proposed multi-parent dynamic nonlinear crossover operator (Alg1, in briefly), genetic algorithm with 2-exchange crossover heuristic crossover (Alg2, in briefly) is used to compare.

Table 1: Comparison Results

Alg	City	Ave	Std
Alg1.	30	440.210205	10.675026
Alg2.	30	481.120557	30.313579
Alg1.	50	447.663086	4.990367
Alg2.	50	505.421631	18.248335
Alg1.	75	593.818311	11.496711
Alg2.	75	600.213623	15.821134
Alg1.	442	5794.257422	130.903159
Alg2.	442	5831.158984	168.262800
Alg1.	10	2.690670	0.000000
Alg2.	10	2.730001	0.041458

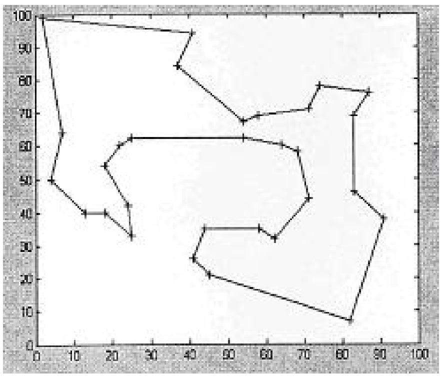

Fig1. Best Solution found with 30 cities

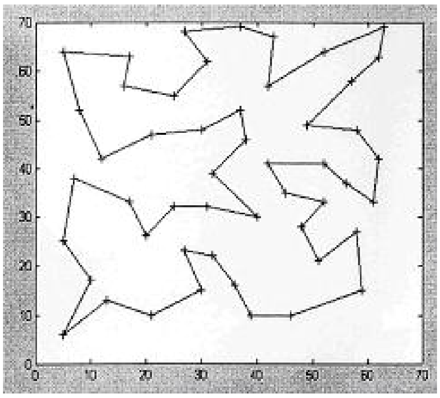

Fig2. Best Solution found with 50 cities

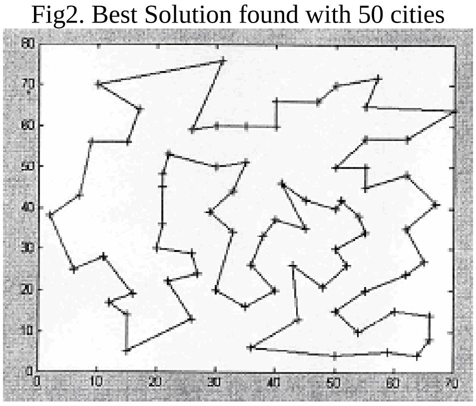

Fig3 Best Solution found with 75 cities

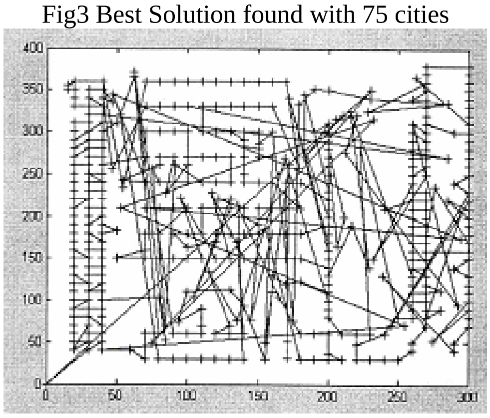

Fig4 Best Solution found with 442 cities

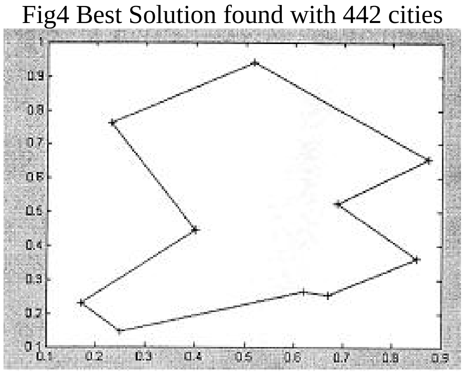

Fig5 Best Solution found with 10 cities

Table 1 provides the comparison results, where Alg represents algorithm, City means the number of city, Ave means the average distance over all 30 runs, and Std means the standard deviation value. Fig.1 to Fig.5 give the best solutions found by our proposed crossover operator. Tab1 and the five figures illustrate the computation efficiency of new multi-parent dynamic nonlinear crossover operator is better.

Acknowledgmen

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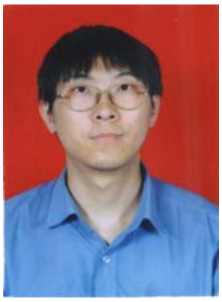

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