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Dynamic multiscale region search algorithm using vitality selection for traveling salesman problem

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ABSTRACT

Traveling salesman problem (TSP) is a classical mathematical model. Many industry, network, and engineering optimization problems on expert and intelligent system are able to be expressed by using TSP-based mathematical model, such as production planning, vehicle routing, resource scheduling, and so on. Vitality selection (VS) is proposed as a new modification scheme based on delete-oldest selection for TSP. The evaluation criterion of individuals in VS is the individual-made progress in the local successive generations. This is different from the pure fitness criterion. Theoretical comparison and behavior feature analysis demonstrate that VS is effective to avoid the premature convergence and escape from the local optimum. On the other hand, dynamic multiscale region search algorithm (DMRSA) using VS is proposed. DMRSA is characterized by the subregion-segmentation and the selected-city methods. These methods for one individual are not only dynamic in one generation, but also variable from the first generation to the last generation. These dynamic-variable search rules are effective to improve the performance of the local search, and different from variable neighborhood search. To demonstrate the effectiveness of DMRSA, experiments about the convergence, the percentage deviation of the average solution to the best known solution, and the average execution time were done. We compared DMRSA with 9 compared algorithms for 27 TSP instances of TSPLIB. DMRSA found the 22 best known solutions for 27 TSP instances. The experiment-proof robustness and adaptability of DMRSA is trustworthy for solving TSP-based mathematical model applications on expert and intelligent system.

1. Introduction

Traveling salesman problem (TSP) is a well-known combinatorial optimization problem, and belongs to NP-complete problems (Rego, Gamboa, Glover, & Osterman, 2011). The objective of TSP is to find the shortest tour for a traveling salesman, who visits each city once and returns to the original city. On the other hand, TSP is also a classical mathematical model for different field optimization problems. Many industry, network, and engineering optimization problems on expert and intelligent system are able to be expressed by using TSP-based mathematical model, such as production planning, vehicle routing, resource scheduling, and so on.

TSP is extensively studied by using Lin-Kernighan, stem-and-cycle methods, evolutionary algorithms (EAs), and so on (Rego et al., 2011). Based on the ensemble and variable neighborhood search (VNS) algorithms, we propose dynamic multiscale region search algorithm (DMRSA) using vitality selection (VS) for solving TSP. The main contributions of VS and DMRSA are summarized as follows.

- There is a Chinese proverb: Race Horses, and Not Observe Horses (RHNOH) (see Section 2.3 for more information). Competition of individuals tells more than observation of individuals only according to fitness. Based on RHNOH, we propose VS as TSP selection. VS selects individuals that make progress in the local successive generations (corresponding to Race Horses). Simultaneously, VS does not select the better fitness individuals only according to fitness (corresponding to Not Observe Horses), if these better fitness individuals make no progress in the local successive generations. The individuals that make progress in the local successive generations generally include rare and valuable edges (RV-edges) for a specific TSP, and have exuberant vitality to promote the population evolution, especially for the premature population (see Section 2.5 for more information).
- TSP heavily depends on edges and regions. DMRSA uses ensemble-branch scheme to improve the adaptability and robustness of DMRSA for solving TSP (see Fig. 6 for more

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information). These ensemble branches, with the gradual and ladder-like parameter structure, implement the multiscale search in DMRSA. Moreover, DMRSA uses dynamic-variable subregion segmentation and selected-city methods to avoid using strong-fixed rules (see Section 3.6 for more information). These multiscale search rules and dynamic-variable search rules are complementary to each other, and improve the performance of the local search in DMRSA.

The rest of the paper is organized as follows. In Section 2, we review the related works of selection schemes, discuss selection schemes, and then introduce VS. In Section 3, we review the related works of TSP solvers, discuss ensemble-based and VNS-based algorithms, and then present DMRSA. In Section 4, we demonstrate the performance of DMRSA by comparing with 9 compared algorithms. In Section 5, we present the concluding remarks and future works.

2. Vitality selection

2.1. Related work

2.1.1. General-purpose selections

The detailed analysis of the general-purpose selections is given in Blickle and Thiele (1996), Goldberg and Deb (1991), and Rogers and Prugel-Bennett (1999), such as proportionate, truncation, and tournament selections. Smith and Vavak (1999) compare a number of selection and replacement strategies in the steady state genetic algorithms. This paper demonstrates that the steady state model is more suited to dynamic environments than the generational model, and ten selection strategies are evaluated, such as delete-oldest selection. Moreover, Smith (2007) analyzes conservative and elitist First-In-First-Out (FIFO, also known as delete-oldest) strategies in terms of models and theoretical indicators. Lozano, Herrera, and Cano (2008) propose the contribution of diversity/replace worst strategy (CD/RW) for steady-state genetic algorithms. CD/RW considers two features of the candidate chromosome to be included into the population: a measure of the contribution of diversity to the population and the fitness function. CD/RW replaces an individual in the population, with a poorer fitness value and with a lower contribution to the population diversity, by an offspring. Hutter and Legg (2006) propose the fitness uniform selection. The fitness uniform selection assumes that the fitness values in the current population are from f_{min} to f_{max}. The fitness uniform selection selects a fitness value f uniformly in the interval [f_{min}, f_{max}]. Then, the individual with fitness nearest to f is selected, and a copy is added to the next generation population.

The evaluation criteria of individuals are the kernel framework basis for the general-purpose selections. According to the evaluation criteria of individuals, the general-purpose selections are classified into the pure fitness-based selections (i.e. proportionate, truncation, and tournament selections), the pure age-based selections (i.e. delete-oldest, conservative FIFO, and elitist FIFO), and the space-mapping-based selections (i.e. CD/RW and fitness uniform selection). The discussions about these general-purpose selections are given in Table 1.

2.1.2. TSP selections

Except for the general-purpose selections, we review TSP selections as follows. Kaya (2011) proposes the back controlled selection. This selection only compares the fitness value of the new individual with the fitness value of the old individual in previous generation. If the fitness value of this new individual is more than the fitness value of the old individual, this new individual will be added to the next generation population. Otherwise, this new individual will be discarded. Tsai, Yang, Tsai, and Kao (2003) propose the heterogeneous pairing selection. Based on the edge similarity for TSP, this selection selects different individuals to perform crossover. This edge similarity mechanism is useful for keeping the population diversity.

Edge is one of the most important concepts for TSP. Unconditionally protecting and rationally assembling valuable edges are a good viewpoint to discuss TSP selections. The discussions about TSP selections are given in Table 2.

2.2. Motivation

Selections are different from reproduction operators, and do not reproduce offspring. In essence, selection schemes only decide the selection model of individuals. Therefore, maximizing the match for other different operators is one of the most important functions of selection schemes. One EA finds the best solution of a specific TSP. This is by no means fortuitous. One of the most fundamental reasons is the best match for other different operators. The best match for other different operators cannot guarantee that one EA finds the best solution. However, a poor match for other different operators must result in finding the poor solutions.

We use the general-purpose selections as the representative of selection schemes, and discuss how to maximize the match for other different operators. As shown in Fig. 1, the general-purpose selections are based on different evaluation criteria of individuals, such as fitness (*Line 1* of Fig. 1), life period (*Line 2* of Fig. 1), and factor indexes in the search and solution spaces (*Line 3* of Fig. 1). These above evaluation criteria of individuals are strong-fixed rules. Sometimes, these strong-fixed rules are not able to maximize the match for other different operators. For example, when the population is premature, one individual makes progress in the local successive generations. However, this individual may be discarded, because this individual is a poor fitness individual, an old individual, or a poor factor index individual.

We propose VS for TSP. VS uses the individual-made progress in the local successive generations as the evaluation criterion of individuals, as shown in *Line 4* of Fig. 1. For example, if an individual makes progress in one generation, this means the better match about this individual for other different operators, and selection scheme should protect this individual. This evaluation criterion of individuals in VS is effective to maximize the match for other different operators.

2.3. Rationality

2.3.1. Assumption

RHNOH is the assumption of vitality for individuals, which is able to distinguish different individuals according to their made progresses in the local successive generations. According to RHNOH, individuals with larger probability of finding the new better solutions are able to be determined approximately. We explain the assumption of vitality for individuals as follows. In this paper, one individual with larger probability of finding the new better solutions is also called that this individual has larger vitality. Otherwise, this individual has smaller vitality.

2.3.2. Definition

We define that the vitality of an individual is the life-expectancy of this individual in the evolution process. The vitality value of an individual expresses the probability of finding the new better solution. The vitality value of an individual is an integer from V_{min} to V_{max}. The initial value of the vitality V_{ini} for the newborn individuals is given by

$$V_{ini} = INT\left(\frac{V_{max} + V_{min}}{2}\right) \tag{1}$$