A Heuristic Oriented Racing Algorithm for the Fine-tuning of Metaheuristics

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Abstract

The metaheuristics have become a powerful tool to solve real-world optimization problems. Its ease adaptability, usually demands effort to correctly define its components (e.g.: problem representation, neighborhood structure, etc.) and parameters to achieve their best performance. Thus, this paper aims to present an approach on the fine-tuning of metaheuristics combining Design of Experiments and Racing algorithms. The key idea is a heuristic method, which explores a search space of parameters looking for candidate configurations near of a promising alternative and consistently finds the good ones. To confirm this approach, we present a case study for fine-tuning a VNS metaheuristic on the classical Traveling Salesman Problem, and compare its results against a well established racing method. In general, our approach proved to be effective in terms of the overall time of the tuning process.

1 Introduction

The algorithms for solving optimization problems, in special the metaheuristics, are highly adaptable to a wide set of problems. However, this feature usually demands a huge effort in the definition of its components (e.g.: problem representation, neighborhood structure, etc.) and parameters to achieve their best performance. Thus, since the last decades there has been a growing academic interests around the automated methods to assist in the fine-tuning of metaheuristics, highlighting the use of Design of Experiments [1, 2, 3], Racing algorithms [4], Neural Networks [5, 6], Fuzzy sets [7], statistical modeling [8, 9] and many others.

In this paper we present an approach on the fine-tuning of metaheuristics combining Design of Experiments (DOE) [10] and Racing algorithms [11, 4] in a heuristic method. The proposed approach brings together some characteristics from different fine-tuning strategies of the literature, such as CALIBRA [12], I/F-Race [13, 4] and ParamILS [14], in a single heuristic method with the ability to define a search space, and the efficiency to focus the search on candidate configurations within the aforementioned search space. To validate our approach, we present a case study with the VNS metaheuristic applied to the classical Traveling Salesman Problem (TSP).

The rest of the paper presents the problem of tuning metaheuristics and our proposed approach (Section 2). The Section 3 brings a case study on the fine-tuning of the VNS metaheuristic by means of different tuning approaches and presents its results. Our final considerations are in Section 4.

2 An Approach on the Fine-tuning of Metaheuristics

In this paper, the problem of fine-tuning of metaheuristics is formalized as: let M be a metaheuristic with a set of parameters, that must be tuned to solve a class of problems P. The parameters of M (e.g.: α, β, ..., ζ) admit a finite set of values (in general, discrete or continuous) and its cardinality can vary according to M and P studied. Let Θ be a set of candidate configurations, such that $\theta \in \Theta$ is any setting of M, then the problem can be formalized as a state-space:

$$S = (\Theta, P) \tag{1}$$

Broadly, the problem consists of knowing which is the best candidate configuration $\theta^* \in \Theta$ to optimize the performance of M on P. However, its determination is not always simple and, in the worst hypothesis, it can requires a full search in S.

2.1 Heuristic Oriented Racing Algorithm

To avoid the full search in S and still find a good setting of M to P, we consider an *agent* (e.g.: a heuristic method) whose the *actions* modify the *state* of S (e.g.: by creating candidate configurations).

Given an initial state (e.g: any alternative in S), the heuristic method explores (1) by creating new candidate configurations at the neighborhood of some best known alternative as a sequence of sets:

$$\Theta_0 \Rightarrow \Theta_1 \Rightarrow \Theta_2 \Rightarrow \ldots$$

From the step k to k+1 the set of candidate configurations is built possibly discarding some inferior alternatives, based on statistical evaluation of a wide range of problems. Given that some candidate configurations persist in that set, they are evaluated on more problem instances. Therefore, search a solution is equivalent to find a path in a graph, that from an initial state reaches the final state, that is, the best setting for M.

This approach is called Heuristic Oriented Racing Algorithm (HORA), due the way for which the alternatives are explored through a heuristic method, and its evaluation process by a racing algorithm.

3 Case Study

The HORA method proposed here can be applied on the fine-tuning of different metaheuristics, regardless its nature or parameters number. To illustrate it, we will use as example the configuration of a basic VNS metaheuristic [15, 16] on instances of the TSP.

The TSP is a NP-hard problem [17] extensively studied in the literature [18, 19], and a standard benchmark for new algorithm ideas. The VNS metaheuristic is a trajectory method widely applied to optimization problems, like the TSP. In summary, its strategy is based on dynamical changes in the neighborhood structure of an incumbent solution, moving to the next one if and only if an improvement is made. At each iteration three important stages must be done: shake, local search and move. A high-level pseudo-code is given in Figure 1.

```
procedure vns(S₀, Kmax)
 S* ← S₀
 repeat
  k ← 1
  repeat
   S′ ← shake(S*, k)
   S′′ ← localSearch(S′)
   S* ← move(S*, S′′, k)
  until k ≤ Kmax
 until termination criteria is met
```

Figure 1: Pseudo-code of the basic VNS metaheuristic.

The considered parameters for the fine-tuning process are in Table 1. The parameters levels (low and high) were chosen on early studies with the metaheuristic.

At the beginning of the tuning process we conduct m experimental studies[1] with DOE on different instances of the TSP from TSPLIB [20]. Its results let us refine the search space of parameters by

1 In this paper, we chosen arbitrarily $m = 5$, in order to promote diversity for the initial search space of parameters. Thus, at the end of the experimental studies we have five different results for each parameter.

defining a more restrict one, bounded by the maximum and minimum values of each parameter in the training set. Accordingly, the new parameter search space is: $n \subset [1621; 3640]$, $k \subset [3; 9]$ and $\delta \subset [2; 4]$.

Parameter	Description	Low	High
n	Number of iterations	1000	5000
k	Number of neighborhood structures	3	9
δ	Length between the neighborhood structures	1	5

Table 1: The parameters of the basic VNS.

The exploration of the new search space is done through HORA by creating alternatives at the neighborhood of some best known candidate configuration. For each of the alternatives, we run the target metaheuristic during 10s on an expanded set of instances[2]. This process was repeated 100 times and the result is presented in terms of mean and standard deviation ($\mu \pm \sigma$) in Table 2.

For comparisons, we chosen a robust fine-tuning method from the literature with a similar evaluation process to that implemented in HORA. Thus, the same tuning process was repeated with a racing algorithm inspired in I/F-Race method [21] (from here on called RACE). However, the following settings have been considered: $n = \{1621; 1909; 2198; 2486; 2775; 3063; 3352; 3640\}$, $k = \{3; 4; 5; 6; 7; 8; 9\}$ and $\delta = \{2; 3; 4\}$. Since of each possible combination of parameters leads to a different configuration for the metaheuristic, there are $8 \times 7 \times 3 = 168$ predefined settings for the VNS in the RACE scenario. The goal is to select an alternative as good as possible, such that it optimizes the performance of the metaheuristic. The result is in Table 2.

Parameter	HORA Settings ($\mu \pm \sigma$)	RACE Settings ($\mu \pm \sigma$)
n	2298 ± 562	2441 ± 634
k	4 ± 1	4 ± 1
δ	3 ± 1	3 ± 1

Table 2: The proposed parameter settings for the basic VNS.

3.1 Experimental Results

The case study results are similar in terms of parameterization (Table 2). However, we emphasize the differences of the tuning process, such as, the average time of the process, with HORA it takes 7872 seconds, whereas with RACE it demands 14392 seconds. The HORA also stands out in terms of the overall number of experiments performed, that is, 781 against 1410 from RACE. At the end of the tuning process, remains on average 8 surviving alternatives for HORA and 40 for RACE.

Even though it is not the main objective of this work, we run the basic VNS for each one of the proposed settings (Table 2) 15 times on 12 instances of the symmetric TSP with the number of cities varying between 300 and 800. Although the median performance from the metaheuristic tuned through HORA is slightly better, the results are statistically similar at the significance level of 5% to the t-Student and Wilcoxon tests.

4 Final Considerations

The HORA method, presented in this paper, combines DOE and Racing algorithm to efficiently search candidate configurations within an improved search space. As shown in the case study (Section 3), its better performance, relative to a classic strategy from the literature, can be explained by the way of it explores the search space. That is, by means of a heuristic method, which seeks for good alternatives in the neighborhood of some best known candidate configuration, and efficiently evaluates them with a racing method. The results achieved show that the proposed approach is a promising and powerful tool mainly when it is considered the overall time of tuning process. Additional studies shown the effectiveness of HORA with other metaheuristics and problems.

2 The expanded set matches 48 instances with less than 1000 cities of the symmetric TSP from TSPLIB.

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