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Performance Analyses of Differential Evolution Algorithm Based on Dynamic Fitness Landscape

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ABSTRACT

Dynamic fitness landscape analyses contain different metrics to attempt to analyze optimization problems. In this article, some of dynamic fitness landscape metrics are selected to discuss differential evolution (DE) algorithm properties and performance. Based on traditional differential evolution algorithm, benchmark functions and dynamic fitness landscape measures such as fitness distance correlation for calculating the distance to the nearest global optimum, ruggedness based on entropy, dynamic severity for estimating dynamic properties, a fitness cloud for getting a visual rendering of evolvability and a gradient for analyzing micro changes of benchmark functions in differential evolution algorithm, the authors obtain useful results and try to apply effective data, figures and graphs to analyze the performance differential evolution algorithm and make conclusions. Those metrics have great value and more details as DE performance.

KEYWORDS

Benchmark Functions, Differential Evolution Algorithm, Dynamic Fitness Landscape Analysis, Global Optimum

1. INTRODUCTION

Differential evolution (DE) (Storn & Price, 1997), one of evolutionary algorithms, proposed by Storn and Price in 1995, is a simple and efficient heuristic for global optimization over continuous spaces. The reason why differential evolution has a doughty ability to handle non-differentiable, non-linear and multimodal cost functions is that it was designed to be a stochastic direct search method which is easily applied to experimental minimization where the cost is derived from a physical experimental rather than a computer simulation. Using a vector population in DE has a great influence in computationally demanding optimizations because the stochastic disturbance of the population vectors can be done

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independently. The differential evolution is an easy and simple programming due to its self-organizing scheme which employs the difference vector of two randomly selected population vectors to disturb an existing vector. Furthermore, the performance of evolutionary algorithms focuses on the convergence property. And there is no doubt that differential evolution has a great convergence property and the convergence speed is extremely rapid.

Differential evolution algorithm is one of the research hotspots in evolutionary computation so far. Most of works about DE are modifying the algorithm and solving problems by these variants. There are few works on DE performance analysis, especially using fitness landscape analysis. This leads to a lack of understanding of DE performance changing during solving process.

In this paper, we are going to apply dynamic fitness landscape to study the performance of traditional differential evolution algorithm through new insights and effective data. According to experiment results, we can see that differential evolution algorithm cannot successfully handle all of benchmark functions which have different fitness landscapes. Different fitness landscapes influence the operators in algorithm and cause algorithm solving the problem successfully or not. The paper is organized as follows: Section 2 introduces the related work of differential evolution algorithm and fitness landscape. Section 3 describes traditional differential evolution algorithm. Analyzing how metrics of fitness landscape could evaluate the performance of differential evolution algorithm and find out the correlation in section 4. Section 5 gives the selected benchmark and evaluation criteria which are based on metrics of dynamic fitness landscape. Experiments are showed through figures, then data and experimental results are summarized in section 6, followed by conclusion and future directions in section 7.

2. RELATED WORK

Recently, fitness landscape is used in many aspects such as search-based software testing problems (Aleti, Moser & Grunske, 2016) producing approximate solutions of a combinatorial optimization problem through climbing combinatorial fitness landscapes (Basseur & Ffon, 2015). Different evolutionary algorithms are improved from different aspects based on traditional algorithms in order to attain better performance including faster convergence speed, fewer parameters, less running time and so on. But here, we are not going to focus on how to improve or propose new algorithms. On the contrary, we are going to employ fitness landscape analysis to study the performance of differential evolution algorithm in many ways. The concept of fitness landscape has been adopted widely in recent years in many fields. (Bolshakov, Pitzer, & Affenzeller, 2011)) considered applying fitness landscape analysis in simulation optimization for meta-optimization purposes and new insights are obtained in the field of fitness landscapes analysis for stochastic problems. (Malan & Engelbrecht, 2013b) proposed using ruggedness, funnels and gradients in the fitness landscapes analyzed and evaluated the performance and the effect of traditional particle swarm optimization (PSO). According to experimental results, these three metrics have valued as part-predictors of PSO performance on unknown problems if used in conjunction with measures approximating other features that have been linked to problem difficulty for PSOs. Meanwhile, they investigated whether a link can be found between problem characteristics and algorithm performance for PSOs. But there are not new insights to show algorithm performance clearly.

3. DIFFERENTIAL EVOLUTION ALGORITHM

Differential evolution algorithm, an evolutionary algorithm, attempts to solve global optimization problems of continuous variable. DE is used for multidimensional real-valued functions but does not use the gradient of the problem being optimized, which means DE does not require for the optimization problem to be differentiable as is required by classic optimization methods such as gradient descent and quasi-newton methods. DE can therefore also be used on optimization problems that are not even