Information Sciences xxx (2015) xxx–xxx

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Across neighborhood search for numerical optimization

Guohua Wu[1,*]

Science and Technology on Information Systems Engineering Laboratory, National University of Defense Technology, Changsha 410073, Hunan, PR China

A R T I C L E I N F O

Article history:
Received 9 March 2015
Revised 14 September 2015
Accepted 27 September 2015
Available online xxx

Keywords:
Across neighborhood search
Evolutionary computation
Swarm intelligence
Numerical optimization

A B S T R A C T

Population-based search algorithms (PBSAs), including swarm intelligence algorithms (SIAs) and evolutionary algorithms (EAs), are competitive alternatives for solving complex optimization problems and they have been widely applied to real-world optimization problems in different fields. In this study, a novel population-based across neighborhood search (ANS) is proposed for numerical optimization. ANS is motivated by two straightforward assumptions and three important issues raised in improving and designing efficient PBSAs. In ANS, a group of individuals collaboratively search the solution space for an optimal solution of the optimization problem considered. A collection of superior solutions found by individuals so far is maintained and updated dynamically. At each generation, an individual directly searches across the neighborhoods of multiple superior solutions with the guidance of a Gaussian distribution. This search manner is referred to as across neighborhood search. The characteristics of ANS are discussed and the concept comparisons with other PBSAs are given. The principle behind ANS is simple. Moreover, ANS is easy for implementation and application with three parameters being required to tune. Extensive experiments on 18 benchmark optimization functions of different types show that ANS has well balanced exploration and exploitation capabilities and performs competitively compared with many efficient PBSAs (Related Matlab codes used in the experiments are available from http://guohuawunudt.gotoip2.com/publications.html).

© 2015 Published by Elsevier Inc.

UNCORRECTED PROOF

1. Introduction

Optimization, including continuous optimization and discrete optimization, or constrained optimization and unconstrained optimization, is frequently involved in many areas, ranging from engineering, management to commercial. Methods for solving optimization problems are referred to as optimization methods. Diverse mathematical programming methods [43], such as fast steepest, conjugate gradient method, quasi-Newton methods, sequential quadratic programming, were first extensively investigated. However, increasing evidences have shown that these traditional mathematical optimization methods are generally inefficient or not efficient enough to deal with many real-world optimization problems characterized by being multimodal, non-continuous and non-differential [61].

In response to this challenge, many population-based search algorithms (PBSAs), including swarm intelligence algorithms (SIAs) and evolutionary algorithms (EAs), have been presented and demonstrated to be competitive alternative algorithms, such as the classical and popular genetic algorithm (GA) [15,16], evolutionary programming (EP) [14,67], particle swarm optimization (PSO) [12,30], differential evolution (DE) [7,49,56] and ant colony optimization (ACO) [2,10]. PBSAs is especially prominent in

* Tel.: +86 15580845945; fax: +86 15580845945.
E-mail address: guohuawu@nudt.edu.cn
[1] This work was partly supported by the National Natural Science Foundation of China under grant no. 61563016, 41571397 and 51178193.

http://dx.doi.org/10.1016/j.ins.2015.09.051
0020-0255/© 2015 Published by Elsevier Inc.

ARTICLE IN PRESS

some optimization areas, such as multiobjective optimization [52,53], multimodal optimization [6,57] and complex constrained optimization [40,54].

We have witnessed that PBSAs have progressed continuously in recent years while gaining great success in real-world applications. However, according to the No Free Lunch (NFL) theorems [58], all search algorithms, including PBSAs, will averagely possess the same performance when they are applied to all possible optimization problems, that is to say, theoretically, there will not exist a general optimization algorithm being superior to all other algorithms. As a result, in addition to the extensive studies on classical PBSAs, new PBSAs with specialized principles and search strategies are emerging more recently to provide more choices for users, such as artificial bee colony (ABC) [1,28], biogeography-based optimization (BBO) [37,48], chemical reaction optimization (CRO) [31,32] and a group search optimizer (GSO) [20].

Roughly speaking, three directions might be deserved to give attention to in order to prompt the progress of evolutionary and swarm intelligence computation. The first direction is associated with the sophisticated modification of existing PBSAs to get performance-enhanced algorithm versions. In fact, we can find that currently, major works on PBSAs are in line with this direction, including the hybridization of different PBSAs [17,26], adaptive parameter control [3,68] and intelligent combination of different search strategies [22,34,60]. The reasonable balance between intensification and diversification, or exploitation and exploration is crucial to improve the efficiency of PBSAs [63].

The second direction attracting researchers' awareness involves the effective integration of problem domain knowledge into PBSAs. Although PBSAs generally do not rely on specific problem domain knowledge, which enables them to be suited to diverse optimization problems, evidences show that the appropriate combination with domain knowledge could often significantly strengthen the performance of PBSAs when dealing with specific problems. For example, the proper use of domain knowledge in ACO application can facilitate to more effective solution representation, neighborhood construction and search strategy design [11,59,65]. In addition, domain knowledge related gradient information and variable relationships were employed in PBSAs for continuous optimization [44,61,64]. Recently, Wu et al. proposed an equality constraint and variable reduction strategy (ECVRS) by employing variable relationships to reduce equality constraints as well as variables of constrained optimization problems [62].

The third direction is the design of new PBSAs. As mentioned before, although various PBSAs have been proposed, the NFL theorems tell that any algorithm cannot be efficient for all optimization problems. To deal with vast number of optimization problems encountered in the real world, new PBSAs with effective and unique optimization strategies are still needed. Generally, to guarantee the contribution of a new PBSA, three standards should be satisfied. First, the principles and concepts behind the new PBSA should be different from other PBSAs. Second, the mechanisms included in the new PBSA should be simple, understandable and easy for application. Third and more importantly, the new PBSA should be better than or at least as competitive as recent popular and efficient PBSA variants.

In this study, the author proposes a novel population-based optimizer named across neighborhood search (ANS). Like other swarm intelligence algorithms (e.g., PSO and ACO), in ANS, a group of individuals search in the solution space with the aim to find the optimal solution of an optimization problem. A memory collection is utilized in ANS to record a certain number of superior solutions found so far by the whole population. At every generation, each individual updates its position by searching across the neighborhoods of multiple superior solutions biased by Gaussian distribution. ANS is very easy and convenient for implementation and application with three parameters requiring adjustments to cater for different optimization problems. Moreover, extensive experiments on various benchmark functions, including unimodal, multimodal and rotated functions, demonstrate that the overall performance of ANS is very competitive compared with several peer PBSAs.

The rest of the paper is structured as follows. Section 2 introduces the new proposed across neighborhood search (ANS), including its motivations, search strategies, convergence process, and algorithmic framework. Section 3 comprehensively discusses the differences between ANS and other major PBSAs. Section 4 reports the experimental results and comparative studies of ANS. Section 5 analyzes the impacts of parameters of ANS. Section 6 concludes this study and gives directions of future research.

2. Across neighborhood search

2.1. Motivations of ANS

Learning from better solutions or individuals is a common technique in PBSAs, though the processes to realize such learning mechanism could be exhibited in different ways for different PBSAs. For example, in PSO, a particle flies in the solution space with a velocity that is guided by the local best solution and global best solution. The learning mechanism is realized during the process that particles fly to local or global best solutions. In GA, EP and DE, at each generation the selection operation is used to retain better solutions while the related crossover and mutation operations based on the retained better solutions actually realize the learning mechanism between better solutions. Although without explicit declaration, these better-solution based learning mechanisms in different PBSAs are all on the basis of following two assumptions.

(1) It has a higher probability to find another better solution around a superior solution in the solution space.
(2) High-quality solutions share similarities with the theoretical optimal solution, namely they have some good solution components (good values for some variables or dimensions, for example).

If the assumptions above hold, to design an effective PBSA, we need to give satisfactory answers to following three questions.

Please cite this article as: G. Wu, Across neighborhood search for numerical optimization, Information Sciences (2015), http://dx.doi.org/10.1016/j.ins.2015.09.051

UNCORRECTED PROOF

Download English Version:

https://daneshyari.com/en/article/6857515

Download Persian Version:

https://daneshyari.com/article/6857515

Daneshyari.com