Information Sciences 340–341 (2016) 175–190

Contents lists available at ScienceDirect

Information Sciences

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

A multi-cycled sequential memetic computing approach for constrained optimisation

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ARTICLE INFO

Article history:
Received 18 October 2014
Revised 30 October 2015
Accepted 2 January 2016
Available online 11 January 2016

Keywords:
Multi-cycled sequential memetic computing approach
Estimation of distribution algorithm
Constrained optimisation

ABSTRACT

In this paper, we propose a multi-cycled sequential memetic computing structure for constrained optimisation. The structure is composed of multiple evolutionary cycles. At each cycle, an evolutionary algorithm is considered as an operator, and connects with a local optimiser. This structure enables the learning of useful knowledge from previous cycles and the transfer of the knowledge to facilitate search in latter cycles. Specifically, we propose to apply an estimation of distribution algorithm (EDA) to explore the search space until convergence at each cycle. A local optimiser, called DONLP2, is then applied to improve the best solution found by the EDA. New cycle starts after the local improvement if the computation budget has not been exceeded. In the developed EDA, an adaptive fully-factorized multivariate probability model is proposed. A learning mechanism, implemented as the guided mutation operator, is adopted to learn useful knowledge from previous cycles.

The developed algorithm was experimentally studied on the benchmark problems in the CEC 2006 and 2010 competition. Experimental studies have shown that the developed probability model exhibits excellent exploration capability and the learning mechanism can significantly improve the search efficiency under certain conditions. The comparison against some well-known algorithms showed the superiority of the developed algorithm in terms of the consumed fitness evaluations and the solution quality.

1. Introduction

The goal of this paper is to develop a memetic algorithm for the constrained optimization problem which is also referred to as nonlinear programming (NLP) [3]. The NLP can be stated as follows:

$$\min f(\mathbf{x}), \mathbf{x} \in \mathcal{F} \in \mathbb{R}^n$$

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http://dx.doi.org/10.1016/j.ins.2016.01.003

where $f(\mathbf{x})$ is the objective function, and $\mathcal{F}$ is the set of *feasible* solutions that satisfies:

$$\begin{cases} g_i(\mathbf{x}) \leq 0, & i = 1, \ldots, q; \\ h_j(\mathbf{x}) = 0, & j = q+1, \ldots, m. \end{cases}$$

Often, a solution $\mathbf{x}$ is regarded as *feasible*, if

$$\begin{cases} g_i(\mathbf{x}) \leq 0 & \forall i = 1, \ldots, q \\ |h_j(\mathbf{x})| - \varepsilon \leq 0 & \forall j = q+1, \ldots, m. \end{cases}$$

where ε is small positive real number. The NLP can then be restated as (cf. (1)):

$$\min f(\mathbf{x}), \mathbf{x} \in \mathcal{F} = \{\mathbf{x} : \hat{g}_i(\mathbf{x}) \leq 0, 1 \leq i \leq m\} \tag{1}$$

where $\hat{g}_i = g_i, 1 \leq i \leq q, \hat{g}_j = |h_j| - \varepsilon, j = q+1, \ldots, m$. Many machine learning problems, such as image processing [68], ordinal regression [17,18], robust clustering [55,57], correlation analysis [58], and others, can be formulated as NLP.

One of the main concerns in developing evolutionary algorithms (EAs) for the NLP is on how to select promising parent individuals for offspring reproduction. An effective selection method, or essentially individual ranking, should balance the feasibility and the objective values of the individuals. Note that an individual with small objective function value might not even be feasible. Most of the selection strategies are based on the superiority of feasible solutions over infeasible solutions [49]. However, Jiao et al. [26] found that global optimal solutions are more likely to be found on the boundary between the non-dominated and feasible sets.

Various constraint-handling techniques have been developed for effective ranking. The stochastic ranking (SR) method [51] ranks the individuals by balancing the objective function value and the penalty on constraint violations stochastically. An addition of ranking method developed in [21] ranks various numerical properties of the population such as the values of the objective functions, the constraint violations, and the number of constraint violations, respectively; and aggregates these rankings together as the final ranking criterion. Some authors, e.g. [1,11], proposed to rank individuals based on Pareto dominance relation in a multi-objective perspective. In [2], the authors proposed to adapt the penalty parameters. In [47], the authors proposed to first identify which constraints are effective and then use them to contribute to the fitness evaluation. In [59], the ε-constraint handling method was proposed in which an ε parameter is applied to control the relaxation of the constrains. A rough penalty method based on the rough set theory was proposed in [32]. The ensembles of these constraint-handling techniques were claimed to reduce the use of fitness evaluations and perform better than algorithms with a single constraint-handling technique in [38]. In [48], the authors studied several existing constraint-handling strategies and proposed several methodologies based on parent-centric and inverse parabolic probability distribution. The authors in [19] found that existing constraint-handling methods are applied to assist but not to guide the search process. They thus proposed the so-called constraint consensus methods to assist infeasible individuals to move towards the feasible region. Interested readers are referred to [41,43] for reviews, and [10,40] for recent advances on constraint-handling.

Another important issue in developing effective EAs for the NLP is on the offspring generation scheme. It is expected that the scheme should be able to explore feasible regions of the NLP in the early stages, and exploit for the global optimum later on. The search abilities of a range of EAs on the NLP (including genetic algorithms [22,63], evolution strategies, evolutionary programming [4], differential evolution [14], particle swarm optimisation [13,20], and many others) have been extensively studied. To the best of our knowledge, the application of EDAs is very limited. In [16], two EDAs coupled with different constraint-handling methods were compared but only on two test problems. The continuous Gaussian model was used in [53] for constrained optimisation.

Besides these research efforts, some researchers have made attempts to develop memetic computing (MC) approaches, i.e. the hybridisation of local optimization and EAs, for the NLP. The MC approach has been well acknowledged as a promising paradigm for dealing with various types of optimization problems [8]. In this paper, we develop a multi-cycled sequential MC framework, where an EDA and a classical constrained optimization algorithm is hybridised sequentially. Further, a simple learning scheme is proposed to learn useful information from previous cycles to improve the search efficiency in latter cycles.

In the rest of the paper, related work on MC is reviewed in Section 2. We then present the multi-cycled sequential MC framework in Section 3. The developed algorithm is presented in Section 4. The experimental results are summarised in Section 5. Section 6 concludes the paper and discusses future work.

2. Related work

The development of the MC approaches has been proceeding in two main directions. On one hand, different meta-heuristics are combined to take advantages of their respective strengths. For example, in [29], a combination of fuzzy logic and evolutionary programming is proposed to handle constraints. In [9], evolutionary programming is hybridized with GENOCOP [42] for the NLP. In [64] and [59], GAs are combined with simulated annealing and PSO, respectively, for the NLP. The integration of artificial bee colony and bees algorithm was presented in [61]. In [23], a novel variant of invasive weed optimization was combined as a local refinement procedure within differential evolution [23]. The combination of variability evolution [35] and CMA-ES [36] was proposed in [37] for the NLP.