Computers and Electrical Engineering 000 (2017) 1–15

Contents lists available at ScienceDirect

Computers and Electrical Engineering

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

Opposition-based learning monarch butterfly optimization with Gaussian perturbation for large-scale 0-1 knapsack problem☆

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ARTICLE INFO

Article history:
Received 3 April 2017
Revised 1 December 2017
Accepted 2 December 2017
Available online xxx

Keywords:
Monarch butterfly optimization
Opposition-based learning
Gaussian perturbation
0-1 knapsack problems

ABSTRACT

Monarch butterfly optimization (MBO) has become an effective optimization technique for function optimization and combinatorial optimization. In this paper, a generalized opposition-based learning (OBL) monarch butterfly optimization with Gaussian perturbation (OMBO) is presented, in which OBL strategy is used on half individuals of the population in the late stage of evolution and Gaussian perturbation acts on part of the individuals with poor fitness in each evolution. OBL guarantees the higher convergence speed of OMBO and Gaussian perturbation avoids to be stuck at a local optimum. In order to test and verify the effectiveness of the proposed method, three groups of 15 large-scale 0-1 KP instances from 800 to 2000 dimensions are used in our studies. The experimental results indicate that OMBO can find high-quality solutions.

1. Introduction

Optimization is one of the oldest sciences which always appear in our scientific research and productive practice. Optimization aims to find the feasible even the best possible solution for a given problem. In the early stage, the deterministic algorithms are usually used to solve low-dimensional, differentiable, continuous optimization problems. Unfortunately, a great number of real world optimization problems are becoming more and more complicated, which is an enormous challenge to the traditional optimization technologies regardless of the quality of solutions or computational time. Under these circumstances, various modern meta-heuristics algorithms are proposed and started to demonstrate their great power when addressing intractable optimization problems and even *NP*-Complete problems [1]. Some of them include genetic algorithm (GA) [2], artificial bee colony (ABC) [3], differential evolution (DE) [4], estimation of distribution algorithm (EDA) [5], harmony search (HS) [6–8], shuffled frog-leaping algorithm (SFLA) [9,10], cuckoo search (CS) [11,12], firefly algorithm (FA) [13],

☆ Reviews processed and recommended for publication to the Editor-in-Chief by Guest Editor Dr. R. C. Poonia.

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https://doi.org/10.1016/j.compeleceng.2017.12.014

fruit fly optimization algorithm (FOA) [14], biogeography-based optimization (BBO) [15,16], earthworm optimization algorithm (EWA) [17], human learning optimization (HLO) [18], krill herd (KH) [19,20,21], and monarch butterfly optimization (MBO) [22,23].

Simulating the migratory behavior of monarch butterflies in nature with the seasons, MBO comes forth as a new biologically inspired computing technique. The original MBO has shown good performance in dealing with numerical optimization [22] and combinatorial optimization problems [23]. However, similar to other meta-heuristics algorithms, MBO also shows a phenomenon of premature convergence and stagnation when addressing complex problems [23]. In order to overcome this important weakness, an opposition-based learning monarch butterfly optimization with Gaussian perturbation (OMBO) is proposed to consider both a solution and its opposite. Theoretically, this strategy may be able to guarantee the fast convergence of OMBO. Moreover, in order to help OMBO escape from local optima, Gaussian perturbation is introduced for the part of the worst individuals. The combinations of these two strategies effectively enhance the global search ability of OMBO. Experimental simulations on three groups of large scale 0-1knapsack problem (0-1 KP) instances demonstrate that OMBO performs well on all the test cases.

The rest of this paper is divided into four sections. In Section 2, the mathematical model of 0-1 KP problem is firstly given. And then monarch butterfly optimization is outlined. This is followed by the descriptions of opposition-based learning and Gaussian perturbation. In Section 3, a hybrid encoding scheme is introduced and a two-stage individual repair and optimization method is described. We elaborate on the procedure of OMBO for the 0-1 KP in detail. In Section 4, an array of comprehensive simulation experiments on three groups of large scale 0-1 KP instances are conducted. Finally, conclusions are provided in Section 5.

2. Review of the related work

2.1. 0-1 knapsack problem

Knapsack problem (KP) is one of the important *NP*-complete problems in computer science and a classical combinatorial optimization problem as well. This problem is derived from resource allocation where there are financial constraints. Since its inception in 1897, KP has been attracted considerable attention in various scientific fields, including combinatorial mathematics, computer science, computational complexity theory, cryptography, etc. Additionally, KP often appears in a variety of decision-making processes in real world, such as investment decision-making [24] and network interdiction problem [25]. The 0-1 KP is the most common among the entire family of KP, in which the number of copies of each kind of item is only limited to 1 or 0. Formally, 0-1 KP is expressed as follows:

Given a set I with n items numbered from 1 to n, each with a weight w_i and a profit p_i, along with a maximum capacity C. Informally, now put items into the knapsack, the target is to maximize the sum of the profits of the items packed into the knapsack, but only if the sum of the weights of the items involved is not more than the knapsack's capacity C. Mathematically, 0-1 KP is to find the maximum value with inequality constraints as follows:

$$\begin{aligned} & Maximize \quad f(x) = \sum_{i=1}^{n} p_i x_i \\ & subject \quad to \quad \sum_{i=1}^{n} w_i x_i \le C, \\ & x_i = 0 \quad or \quad 1, \quad i = 1, \ldots, n, \end{aligned} \tag{1}$$

where the binary variable $x_i$indicates the selection of items. x_i=1 indicates that item i is loaded into the knapsack, otherwise, x_i=0.

2.2. Monarch butterfly optimization

Based on the characteristics of monarch butterfly behavior, MBO, as one of the most effective swarm intelligence algorithm, is recently proposed. Different from most evolutionary algorithms, MBO divides the entire population into two subpopulations named subpopulation_1 and subpopulation_2, respectively. The total number of the population is NP. The number of individuals of subpopulation_1 is NP_1 and the number of individuals of subpopulation_2 is NP_2. Meanwhile, there are two search operators, i.e., migration operator and butterfly adjusting operator. Migration operator updates the individual information of subpopulation_1, while butterfly adjusting operator acts on all individuals of subpopulation_2. The main character of butterfly adjusting operator is that the beneficial information of the global best monarch butterfly may influence the quality of the new individuals. Additionally, as an effective way of random walk, Lévy flights are used to improve searching efficiency and quality. More detailed description about MBO algorithm can be referred as [22].

2.2.1. Migration operator

For individual i in subpopulation_1, the position from generation t to t+1 can be updated by Eq. (2):

$$x_{i,k}^{t+1} \leftarrow \begin{cases} x_{r1,k}^{t}, & if \quad r \le p \\ x_{r2,k}^{t}, & else \end{cases} \tag{2}$$