Information Sciences 320 (2015) 126–139

Contents lists available at ScienceDirect

Information Sciences

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

An adaptive simplified human learning optimization algorithm

Ling Wang [a,*], Haoqi Ni [a], Ruixin Yang [a], Panos M. Pardalos [b], Xin Du [a], Minrui Fei [a]

[a] Shanghai Key Laboratory of Power Station Automation Technology, School of Mechatronics Engineering and Automation, Shanghai University, Shanghai 200072, China

[b] Center for Applied Optimization, Department of Industrial and Systems Engineering, University of Florida, Gainesville, FL 32611, USA

ARTICLE INFO

Article history:
Received 27 November 2014
Received in revised form 23 March 2015
Accepted 11 May 2015
Available online 16 May 2015

Keywords:
Human learning optimization
Meta-heuristic
Global optimization
Social learning
Individual learning

ABSTRACT

This paper presents a novel meta-heuristic optimization algorithm, named Adaptive Simplified Human Learning Optimization (ASHLO), which is inspired by the human learning mechanisms. Three learning operators, i.e. the random learning operator, the individual learning operator, and the social learning operator, are developed to generate new solutions and search for the optima by mimicking the learning behaviors of humans. The numerical functions, deceptive functions and 0–1 knapsack problems are adopted as benchmark problems to validate the performance of ASHLO, and the results are compared with those of binary particle swarm optimization (BPSO), modified binary differential evolution (MBDE), the binary fruit fly optimization algorithm (bFOA) and adaptive binary harmony search (ABHS). The experimental results demonstrate that the developed ASHLO significantly outperforms BPSO, MBDE, bFOA and ABHS and has a robust search ability for various problems. With the adaptive strategy, the search ability of ASHLO is improved further especially on the high-dimensional and complicated problems. Considering the ease of implementation, the excellence of global search ability and the robustness for various problems, ASHLO is a promising optimization tool for scientific research and engineering applications.

© 2015 Elsevier Inc. All rights reserved.

1. Introduction

Over the last five decades, a large number of algorithms have been developed to solve various optimization problems [27,10]. Numerical linear and nonlinear programming methods form the basis for most of these algorithms, which require substantial gradient information and usually seek to improve the solution in the neighborhood of a starting point [20]. Although these numerical optimization algorithms provide a useful strategy to obtain the global optimum in simple and ideal models, many real-world engineering optimization problems, however, are typically complex and large scale, and the evaluation of the functions and gradients is expensive due to their implicit dependence on design variables, which are quite difficult to be solved by using these algorithms [28]. It is well known that classical derivative-based optimization techniques need a well-defined starting point which should be significantly close to the final solution, otherwise they are very likely to get trapped in a local optimum [2]. The computational drawbacks of existing derivative-based numerical methods such as complex derivatives, sensitivity to initial values, and the large amount of enumeration memory required have forced researchers to study meta-heuristic algorithms, such as Genetic Algorithms [13,14], Tabu Search [12], Ant Colony

* Corresponding author.
E-mail address: wangling@shu.edu.cn (L. Wang).

http://dx.doi.org/10.1016/j.ins.2015.05.022
0020-0255/© 2015 Elsevier Inc. All rights reserved.

Optimization [4], Particle Swarm Optimization [18], Harmony Search [20,22], Hunting Search Algorithms [25], Chemical Reaction Optimization Algorithms [19], Gravity Algorithms [21], Fruit Fly Optimization Algorithms [26], Cuckoo Search [35], Bat Algorithms [36], and Firefly Algorithms [37,17], to solve complicated optimization problems.

To solve hard optimization problems more effectively and efficiently, new powerful meta-heuristics inspired by nature, especially by biological systems, must be explored, which is a hot topic in evolutionary computation community [9]. As is known to all, human being is the smartest creature in the earth, and the strongest learning ability of humans makes us be able to solve a large number of complicated problems that other living beings, such as birds, ants, and fireflies, cannot tackle. Many human learning activities are similar to the search process of meta-heuristics. For instance, when a person learns how to play Sudoku, he or she repeatedly practices to improve new skills and evaluates his or her performance for guiding the following study while meta-heuristics iteratively generate new solutions and calculate the corresponding fitness for adjusting the following search. The process of human learning is extremely complicated and its study is the part of neuropsychology, educational psychology, learning theory, and pedagogy. However, in most activities humans solve problems by the random learning strategy, the individual learning strategy, and the social learning strategy [31]. For the example of learning Sudoku again, a person may learn randomly due to the lack of prior knowledge or exploring new strategies (random learning), learn from his or her previous experience (individual learning), and learn from his or her friends and books (social learning). Inspired by this simple learning model, an Adaptive Simplified Human Learning Optimization algorithm (ASHLO) is presented in this paper.

The rest of the paper is organized as follows. Section 2 introduces the idea, operators and implementation of ASHLO in detail. Then, the presented ASHLO is applied to tackle a suit of numerical benchmark functions, deceptive problems, and 0–1 knapsack problems to evaluate its performance. Finally, Section 4 concludes the paper.

2. Adaptive simplified human learning optimization algorithm

In ASHLO, three learning operators, i.e. the random learning operator, the individual learning operator, and the social learning operator, are used to yield new candidates to search for the optima, which simulates the human learning process.

2.1. Initialization

The binary-coding framework is adopted in ASHLO, and consequently an individual is represented by a binary string as Eq. (1),

$$x_i = [x_{i1} \quad x_{i2} \quad \cdots \quad x_{ij} \quad \cdots \quad x_{iM}], \quad x_{ij} \in \{0,1\}, \; 1 \leqslant i \leqslant N, \; 1 \leqslant j \leqslant M \tag{1}$$

where x_i denotes the i-th individual, N is the size of population, and M is the dimension of the solution. Each bit of a binary string is initialized as "0" or "1" randomly, which stands for a basic element of the knowledge or skill that people want to learn and master. After generating N individuals, an initial population is obtained as Eq. (2) for solving problems.

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_i \\ \vdots \\ x_N \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1M} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2M} \\ \vdots & \vdots & & \vdots & & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{iM} \\ \vdots & \vdots & & \vdots & & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{Nj} & \cdots & x_{NM} \end{bmatrix} \tag{2}$$

2.2. Learning operators

2.2.1. Random learning operator

At the beginning of learning processes, people usually learn at random as there is no prior knowledge of problems. In the following studying, due to interference, forgetting, only knowing partial knowledge of problems and other factors [24], individuals cannot fully replicate previous experience and therefore they still learn with a certain randomness. On the other hand, during the learning process, people also keep exploring new strategies to solve problems better. Thus random learning always accompanies in the learning process of humans which is of importance, just as Cziko [5] presented that human learning is the results of "random variation and universal selection". To emulate these phenomena of randomness of human learning, a simplified random learning operator is used in ASHLO as Eq. (3).

$$x_{ij} = Rand(0,1) = \begin{cases} 0, & 0 \leqslant rand() \leqslant 0.5 \\ 1, & else \end{cases} \tag{3}$$

where $rand()$ is a stochastic number between 0 and 1.

Download English Version:

https://daneshyari.com/en/article/392009

Download Persian Version:

https://daneshyari.com/article/392009

Daneshyari.com