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A human learning optimization algorithm and its application to multi-dimensional knapsack problems

Ling Wang [a,*], Ruixin Yang [a,b], Haoqi Ni [a], Wei Ye [a], Minrui Fei [a], Panos M. Pardalos [c]

[a] Shanghai Key Laboratory of Power Station Automation Technology, School of Mechatronics and Automation, Shanghai University, Shanghai 200072, China
[b] Computer Science Department, North Carolina State University, Raleigh, NC 27695, USA
[c] Center for Applied Optimization, Department of Industrial and Systems Engineering, University of Florida, Gainesville, FL 32611, USA

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ABSTRACT

Inspired by human learning mechanisms, a novel meta-heuristic algorithm named human learning optimization (HLO) is presented in this paper in which the individual learning operator, social learning operator, random exploration learning operator and re-learning operator are developed to generate new solutions and search for the optima by mimicking the human learning process. Then HLO is applied to solve the well-known 5.100 and 10.100 multi-dimensional knapsack problems from the OR-library and the performance of HLO is compared with that of other meta-heuristics collected from the recent literature. The experimental results show that the presented HLO achieves the best performance in comparison with other meta-heuristics, which demonstrates that HLO is a promising optimization tool.

1. Introduction

Optimization problems are wide-ranging and plentiful in our daily life, and therefore methods for solving these problems have been a widely researched topic [1,2]. Traditional gradient-based algorithms like the steepest descent method and the Newton method have been used to solve various optimization problems successfully. However, these approaches heavily rely on the initial starting point, the topology of the feasible region and the surface associated with objective functions [3]. Inspired by physical and biological systems, various meta-heuristics have been developed to deal with complex optimization problems. For instance, genetic algorithms [4] mimic the evolution of living organisms with genetic operators such as the reproduction, crossover and mutation. Simulated annealing [5] resembles the cooling process of molten metals through annealing. Ant Colony Optimization (ACO) [6] takes inspiration from the foraging and path making behaviors of ants. Particle swarm optimization (PSO) [7] copies the behaviors of birds searching for food in a collaborative way. Artificial fish-swarm algorithm [8] imitates the fish-swarm behaviors like the praying behavior, swarming behavior and chasing behavior. Immune algorithm [9] emulates the defense process of the immune system against its invaders in a biological body. Bees Swarm Optimization [10] models the behaviors of honey bees collecting, processing and advertising of nectars. Compared with traditional gradient-based algorithms, these nature-inspired algorithms can tackle NP-hard problems more effectively and efficiently with the advantages of broad applicability, flexibility and ease of implementation. Therefore, meta-heuristic design has been drawing increasing attention from researchers, and novels algorithms have been presented in the latest decade such as the biogeography-based optimization algorithm [11], harmony search (HS) [12], the hunting search algorithm [13], the chemical reaction optimization algorithm [14] and the gravity algorithm [15]. However, most of these algorithms are originally designed to solve the continuous or discrete problems which cannot be directly applied to binary-coding problems such as feature selection and knapsack problems, and therefore various binary variants like the discrete binary PSO algorithms [16,17], discrete binary differential evolution algorithms [18–20], binary HS [21,22] and binary gravitational search algorithm [23] are proposed to extend the applications of algorithms.

Compared with real-coded or discrete-coded optimization algorithms, only a few binary-coded algorithms have been proposed in recent years while more and more complicated binary-coding problems arise. On the other hand, for many engineering problems with low precision like the design of controllers [24], binary-coding algorithms may perform better than real-coded algorithms in terms of search accuracy and the convergence speed as infinite search space is mapped into finite solution space. In addition, binary algorithms can be easily used to solve hybrid-coded problems in which real variables, discrete variables and binary variables are included, which is an advantage for engineering applications. Thus, it is essential to develop efficient and effective binary-coded optimization tools. Inspired by human learning mechanisms, a new meta-heuristic algorithm called human learning optimization (HLO) algorithm is presented and applied to multi-dimensional knapsack problems in this work.

The rest of the paper is organized as follows. Section 2 introduces the presented HLO in detail. In Section 3, HLO is applied to multi-dimensional knapsack problems and the results are compared with those of other meta-heuristics collected from recent works to validate its performance. Finally, Section 4 concludes the paper and explains our future work.

2. Human learning optimization algorithm

In nature, human learning is an iterative optimization process. People master and improve their skills by learning repeatedly on some complicated tasks and activities such as playing basketball and learning dancing, which is similar to meta-heuristics searching for the global optima iteratively. There are various theories of

* Corresponding author. Tel.: +86 18321369525.
E-mail address: wangling@shu.edu.cn (L. Wang).

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learning such as individual learning theories, social learning theories and cognitive learning theories. Meanwhile, many factors like the emotional factor and the social factor affect the learning process. The process of human learning is extremely complicated and its study is the part of neuropsychology, educational psychology, learning theory and pedagogy. However, the HLO presented in this paper is built on a simple learning model for easy implementation and four learning operators named the individual learning operator, social learning operator, random exploration learning operator and re-learning operator are designed to search for the optima which imitate the mechanisms commonly existing in the learning process of humans. For instance, a person learns playing basketball through self-practicing (individual learning) and from his or her coach (social learning). During the learning process, he or she may try new strategies to improve his or her skill further which are characterized by randomness due to the absence of prior-knowledge (random exploration learning) and re-learns with new approaches (re-learning) when he or she hits and cannot pass the bottleneck of learning.

2.1. Initialization

HLO adopts the binary-coding framework in which each bit corresponds to a basic component of knowledge for solving problems. Therefore, an individual, i.e. a candidate solution, is represented by a binary string as Eq. (1) which is initialized as “0” or “1” randomly assuming that there is no prior-knowledge of problems,

$$x_i = \begin{bmatrix} x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{iM} \end{bmatrix}, \ 1 \le i \le N, 1 \le j \le M \tag{1}$$

where x_i is the ith individual, N is the number of individuals of the population, and M is the number of components contained in the knowledge, i.e. the dimension of solutions. After initializing all the individuals, the initial population of HLO is generated as Eq. (2).

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_i \\ \vdots \\ x_N \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1M} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2M} \\ \vdots & \vdots & & \vdots & & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{iM} \\ \vdots & \vdots & & \vdots & & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{Nj} & \cdots & x_{NM} \end{bmatrix} \tag{2}$$
$$x_{ij} \in \{0, 1\}, \quad 1 \le i \le N, 1 \le j \le M$$

2.2. Learning operators

2.2.1. Individual learning operator

Every person learns in conscious or unconscious states, which is a fundamental requirement of existence. Individual learning is defined as the ability to build knowledge through individual reflection about external stimuli and sources. In HLO, an individual learns to solve problems by the individual learning operator based on its own experience which is stored in the Individual Knowledge Database (*IKD*) as Eqs. (3) and (4).

$$x_{ij} = ik_{ipj} \tag{3}$$

$$IKD_i = \begin{bmatrix} ikd_{i1} \\ ikd_{i2} \\ \vdots \\ ikd_{ip} \\ \vdots \\ ikd_{iG} \end{bmatrix} = \begin{bmatrix} ik_{i11} & ik_{i12} & \cdots & ik_{i1j} & \cdots & ik_{i1M} \\ ik_{i21} & ik_{i22} & \cdots & ik_{i2j} & \cdots & ik_{i2M} \\ \vdots & \vdots & & \vdots & & \vdots \\ ik_{ip1} & ik_{ip2} & \cdots & ik_{ipj} & \cdots & ik_{ipM} \\ \vdots & \vdots & & \vdots & & \vdots \\ ik_{iG1} & ik_{iG2} & \cdots & ik_{iGj} & \cdots & ik_{iGM} \end{bmatrix} \tag{4}$$
$$1 \le i \le N, 1 \le p \le G, 1 \le j \le M$$

where IKD_i is the individual knowledge database of person i, G denotes the size of the *IKDs*, ikd_{ip} stands for the pth best solution of person i, and p, a random integer, determines which individual in the *IKD* is adopted for individual learning.

2.2.2. Social learning operator

Social learning is a transmission of knowledge and skills through direct or indirect interactions among individuals. In the social context, people can learn from not only their own direct experience but also the experience of the other members, and therefore they can develop further their abilities and achieve the higher efficiency with an effective knowledge sharing. To possess the efficient search ability, the social learning mechanism is mimicked in HLO. Like human learning, each individual of HLO studies the social knowledge stored in the Social Knowledge Database (SKD) with some probability as Eqs. (5) and (6) when it yields a new solution,

$$x_{ij} = sk_{qj} \tag{5}$$

$$\mathrm{SKD} = \begin{bmatrix} skd_1 \\ skd_2 \\ \vdots \\ skd_q \\ \vdots \\ skd_H \end{bmatrix} = \begin{bmatrix} sk_{11} & sk_{12} & \cdots & sk_{1j} & \cdots & sk_{1M} \\ sk_{21} & sk_{22} & \cdots & sk_{2j} & \cdots & sk_{2M} \\ \vdots & \vdots & & \vdots & & \vdots \\ sk_{q1} & sk_{q2} & \cdots & sk_{qj} & \cdots & sk_{qM} \\ \vdots & \vdots & & \vdots & & \vdots \\ sk_{H1} & sk_{H2} & \cdots & sk_{Hj} & \cdots & sk_{HM} \end{bmatrix} \tag{6}$$
$$1 \le q \le H, 1 \le j \le M$$

where H is the size of the SKD and skd_q represents the qth social knowledge in the SKD, that is, the new generated candidate x_i randomly chooses one of best solutions stored in the SKD and copies the corresponding bit.

2.2.3. Random exploration learning operator

Anyway, people cannot always reproduce their own experience or social knowledge perfectly during the learning process due to various factors such as the disturbance and forgetting, and consequently a random learning is acted. Moreover, human also keeps trying various new strategies to improve performance. And as usually there is no prior knowledge for a new problem, this exploration procedure is characterized by randomness. Simulating these phenomena, HLO performs the random exploration learning with some probability as Eq. (7)

$$x_{ij} = RE(0, 1) = \begin{cases} 0, & rand < 0.5 \\ 1, & else \end{cases} \tag{7}$$

where *rand* is a random number in [0, 1).

2.2.4. Re-learning operator

In HLO, an individual is considered of hitting the bottleneck if its fitness is not improved in the certain number of generations. In this case, the re-learning operator is activated which clears the IKD of the corresponding individual so that it can re-learn with