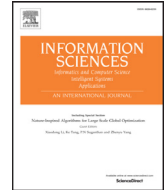




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Learning backtracking search optimisation algorithm and its application

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ABSTRACT

The backtracking search algorithm (BSA) is a recently proposed evolutionary algorithm (EA) that has been used for solving optimisation problems. The structure of the algorithm is simple and has only a single control parameter that should be determined. To improve the convergence performance and extend its application domain, a new algorithm called the learning BSA (LBSA) is proposed in this paper. In this method, the globally best information of the current generation and historical information in the BSA are combined to renew individuals according to a random probability, and the remaining individuals have their positions renewed by learning knowledge from the best individual, the worst individual, and another random individual of the current generation. There are two main advantages of the algorithm. First, some individuals update their positions with the guidance of the best individual (the teacher), which makes the convergence faster, and second, learning from different individuals, especially when avoiding the worst individual, increases the diversity of the population. To test the performance of the LBSA, benchmark functions in CEC2005 and CEC2014 were tested, and the algorithm was also used to train artificial neural networks for chaotic time series prediction and nonlinear system modelling problems. To evaluate the performance of LBSA with some other EAs, several comparisons between LBSA and other classical algorithms were conducted. The results indicate that LBSA performs well with respect to other algorithms and improves the performance of BSA.

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1. Introduction

For some science and engineering problems that can be converted to optimisation problems, the search for and design of better optimisation algorithms has never ceased. To solve complex problems such as nonlinear, non-differentiable, and non-convex objective function problems, researchers have focused on designing novel evolutionary algorithms (EAs) or improving the performance of existing algorithms. Of these algorithms, swarm intelligence optimisation algorithms and genetic evolution algorithms play very important roles in the solution of complex optimisation problems. The particle swarm optimisation (PSO) algorithm [12], which mimics the foraging law of birds, has been successfully used in function optimisation [37], sequence classification problems [36], and power output systems [25]. Some variants of PSO, such as the fully informed particle swarm (PSOFIPS) [20], fitness-distance-ratio-based PSO (PSOFDR) [23], and comprehensive learning particle swarm (CLPSO) [15], have also been proposed to improve the performance of PSO and solve optimisation problems. Moreover, some

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hybrid algorithms are also introduced to improve the performance of PSO [13,21], and some discrete methods are proposed to extend the application domain of PSO [2,8,10]. Simulating the teaching-learning process in a class, the teaching-learning-based optimisation (TLBO) algorithm [31] has also been proposed. There are fewer parameters that must be determined in its updating equations, and the algorithm is easily implemented. To make full use of the advantages of TLBO, two approaches have been taken: one is to improve the efficiency of the algorithm by modifying the updating process or combining it with other EAs, and the other is to extend its application domains. The concept of elitism has been utilised in elitism TLBO (ELTBO) to improve its performance by replacing some worst learners in the class by elitisms [29]. A self-learning TLBO that designs a new self-learning method has been used to train the radial basis function (RBF) neural modelling of batteries [41]. Many teachers, an adaptive teaching factor, tutorial training, and self-motivated learning have all been used to improve the diversity of the population [30]. These modified TLBO algorithms perform well for some optimisation problems. With respect to the application fields, the Lévy mutation operator [7] has been used to help TLBO avoid local optima, and the new algorithm has successfully been used for the IEEE 30-bus test system. An improved TLBO [6] with direction angle has been introduced to increase the searching ability of its learners, and it has been combined with a double differential evolution algorithm to handle the optimal reactive power dispatch (ORPD) problem. Local and self-learning methods [3] have been used to improve the performance of the original TLBO, and these approaches display some good performance for global optimisation problems. The multi-objective teaching-learning optimiser [19] has been used for handling reactive power systems. The optimisation of plate-fin heat exchangers [22] and modern machining processes [28], short-term hydrothermal scheduling problems [32], two-stage thermoelectric coolers [27], and flow-shop rescheduling problems [11,14] have all been solved by TLBO. A detailed review of applications of TLBO can be found in [26]. Simplifying the training process and decreasing the number of undetermined parameters of intelligence optimisation algorithms are very important issues. To address them, a novel algorithm called the backtracking search algorithm (BSA) [5] was proposed in 2013 and used for some engineering optimisation problems. BSA has been used for surface wave analysis [34] and to solve concentric circular antenna array synthesis optimisation problems [9]. BSA and differential evolution algorithm (DE) have also been combined to solve unconstrained optimisation problems [40]. The oppositional BSA [17] was introduced to solve hyper-chaotic system parameter identification optimisation problems. The BSA with three constraint handling methods [43] was used for solving constrained optimisation problems. Compared to some classical EAs, BSA is a very new optimisation algorithm, and the improved variants of BSA are relatively few.

As mentioned above, BSA and TLBO have both shown to be superior at solving some optimisation problems, especially because the algorithms are simple and there are few undetermined parameters in the individual updating equations. As young algorithms, their performance at solving complex problems needs to be improved. Their disadvantages are detailed in Sections 2 and 3.

To improve the global performance of BSA, a new method that combines the ideas of TLBO and BSA is presented in this paper. The main contributions of the new method are as follows. The first contribution is the addition of learning guidance in the BSA updating equations to improve convergence speed of BSA. The second is the integration of three learning methods into one equation to update parts of individuals according to a random probability. Another contribution is the avoidance of the use of the worst individual in order to improve the diversity of the population. In contrast to the two function evaluations (FEs) for an individual in a generation of the TLBO algorithm, there is only one FE per generation in the new method. Hence, the computation cost for a generation of the proposed algorithm is less than that of TLBO.

The rest of the paper is organised as follows: the basic BSA and original TLBO are briefly introduced in Section 2 and Section 3, respectively; LBSA is presented in Section 4; the benchmark functions in CEC2005 and CEC2014 are tested to show the effectiveness of different algorithms in Section 5; the applications for two typical nonlinear modelling problems and chaotic time series prediction problems are displayed in Section 6; and conclusions are given in Section 7.

2. Basic BSA

The BSA is a population-based EA that is developed from a DE algorithm, but it is not the same as DE. It contains five processes: initialisation, selection-I, mutation, crossover, and selection-II. There are two populations in BSA: one is the evolution population and the other is the trial population. The trial population is composed of some historical information regarding the evolution population, and a search-direction matrix is built by the two populations to update the positions of the individuals. There is only one control parameter, namely the *mix rate*, which controls the number of individual elements that will be mutated in a trial. The five steps of BSA are simply described as follows, and further details can be found in [5].

- (1) **Initialisation.** The initial population and history population of BSA are initialised according to Eq. 1 and 2, where U is the uniform distribution, and low_j and up_j are the low and up boundaries of variables.

$$P_{i,j} \sim U(low_j, up_j) \quad (1)$$

$$oldP_{i,j} \sim U(low_j, up_j) \quad (2)$$

where i is the i th individual of the population, $i=1, 2, \dots, N$, N is the population size, j is the j th bit of the i th individual, $j=1, 2, \dots, D$, and D is the dimension size of variables.

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