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A hybrid co-evolutionary cultural algorithm based on particle swarm optimization for solving global optimization problems

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ABSTRACT

Intelligent evolutionary algorithms have been widely used to solve large-scale, complex global optimization problems. Co-evolutionary algorithm (CEA), cultural algorithm (CA), and particle swarm optimization (PSO) are all promising methods in the field of intelligent computation. In this paper, a hybrid co-evolutionary cultural algorithm based on particle swarm optimization (CECBPSO) is proposed. In CECBPSO, a novel space called shared global belief space (SGBS) is introduced into the co-evolutionary mechanism, and a new co-evolutionary cultural framework is built. Through the synergistic mechanism, the algorithm has higher probability of avoiding local optima and the whole swarm can find global optima more quickly. Factorial Design (FD) approach is used in this paper in order to get a guideline on how to tune the designed parameters in CECBPSO. Extensive computational studies are also carried out to evaluate the performance of CECBPSO on thirteen benchmark functions and three real-life optimization problems. The results show that the proposed algorithm has superior performance to other compared algorithms in terms of accuracy and convergence speed, especially on high-dimensional problems.

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1. Introduction

In recent years, as a new class of optimization algorithms, evolutionary algorithms have been paid more and more attention. Compared with traditional mathematic methods, intelligent evolutionary algorithms have achieved great success on solving complex, nonlinear, discrete optimization problems [1].

Particle swarm optimization (PSO) [2,3], which was proposed by Kennedy and Eberhart in 1995, is a kind of evolutionary algorithm based on swarm intelligence. It was inspired by the social behavior of birds foraging. Compared with genetic algorithm (GA), PSO uses a velocity-position model without complex genetic operations. Therefore, it has excellent efficiency. Because of its simplicity and easiness in implementation, PSO has attracted more and more attention, and has been applied in many areas, such as multi-dimensional optimization problem, neural network training, fuzzy control system designs [4–13].

However, basic PSO still can be improved. Accelerating convergence speed and avoiding local optima are the two most important and appealing goals in PSO researches [14]. In recent years, a large number of approaches have been developed to improve the efficiency of the algorithm to achieve these two goals. In these developments, control of algorithm parameters, combination with auxiliary search operators and topological structure improvement are three most salient and promising approaches [15]. Liu et al. [16] proposed a hybrid PSO algorithm named CPSO which integrated chaotic local searching behavior into PSO. Compared with basic PSO, CPSO is superior in term of searching quality, efficiency and robustness. Xu and Gu [17] incorporated PSO and differential evolution (DE), and proposed a hybrid algorithm called PSOPDE. Simulation results suggest that PSOPDE behaves better and has higher efficiency. Liang et al. [18] proposed comprehensive-learning PSO (CLPSO) to improve PSO on avoiding local optima. However, it is seen to be difficult to achieve both of the two goals simultaneously. Many of the PSO improvements can help the algorithms get better optima, but meanwhile, make the convergence speed slower.

Cultural algorithm (CA) was firstly purposed by Reynolds [19] in 1994. It was inspired by human sociology and developed in order to model the evolution of the cultural component of an evolutionary computational system over time as it accumulates experience [20]. CA simulates the social and cultural changes. The individuals of cultural algorithm are divided into two parts: population space and belief space. The two spaces evolve respectively and communicate with each other through specific protocols. As a result, CA can provide an explicit mechanism for global knowledge and a useful algorithm framework which to model self-adaptation in an evolutionary or swarm intelligence system

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[21–23], such as genetic algorithm (GA) [24], particle swarm optimization (PSO) [25], ant colony optimization (ACO) [26], differential evolution (DE) [27]. The dual inheritance enhances the efficiency of the algorithm.

Many researchers devote to improve the evolutionary algorithms mentioned above and have proposed a lot of promising methods. However, the experiment results are still not satisfying for large-scale complex real-world problems. Each algorithm above has only one population, and the influence of other existing populations or outer environment is ignored. In order to overcome this obstacle, a concept called "co-evolution" is introduced into intelligent computation field. The original idea of co-evolution was first proposed by Darwin [28], and used to describe the mutual influences in evolving processes of different species. Co-evolutionary algorithm (CEA) is a kind of new evolution algorithm on the base of co-evolutionary theory. Generally, CEA can be divided into two kinds: Cooperative Co-evolutionary Algorithm (CoopCEA) and Competitive Co-evolutionary Algorithm (CompCEA). CoopCEA [29,30] was firstly proposed by M.A. Potter and K.A.D. Jong in 1994. The universal model of CoopCEA was put forward in 2000 [31]. C.D. Rosin and R.K. Belew published the research of CompCEA in 1995 [32]. CEA overcomes many disadvantages of traditional evolution algorithm, hence more and more scholars devote to this field. But, currently, there has not been a unified framework of CEA. Researchers in different fields often set up their own models and algorithms under co-evolution framework according to their own ideas [33–35].

In this paper, in order to fully use the advantages of PSO, CA and CEA, a hybrid Co-Evolutionary Cultural algorithm Based on Particle Swarm Optimization (CECBPSO) is proposed. In CECBPSO, a co-evolutionary mechanism between two cultural algorithms is built and PSO is introduced into the framework of CA. In the hybrid algorithm, a special set of individuals called shared global belief space (SGBS) is designed to coordinate knowledge and experience of the populations. And some new strategies are proposed to increase the diversity of individuals. Besides, a number of tests on parameter selection are done through an orthogonal experiment. Based on the results, a guideline on how to tune the parameters in CECBPSO to achieve good performance is given.

The remainder of this paper is organized as follows. In Section 2, we provide a brief survey of researches on PSO, CA and CEA. The proposed algorithm CECBPSO is introduced in Section 3. The tests on parameter selection are presented and discussed in Section 4. Experimental results demonstrating the performance of CECBPSO in comparison with several other algorithms over a suite of optimization problems are presented in Section 5. Finally, conclusions are drawn in Section 6.

2. Brief description of PSO, CA and CEA

2.1. Particle swarm optimization (PSO)

In basic PSO, proposed by Kennedy and Eberhart, a group of "birds" (i.e. particles) are represented as potential solutions. Each particle updates in the solution space according to some rules just like a bird searching for food, and ultimately stays in the best position. Initially, particles are initialized by a group of random velocities and positions within the corresponding ranges. Then particles update their velocities and positions as follows:

$$v_{id}^{k+1} = wv_{id}^k + c_1 r_1 (p_{id}^k - x_{id}^k) + c_2 r_2 (p_{gd}^k - x_{id}^k) \tag{1}$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \tag{2}$$

where v_{id}^k and x_{id}^k are the velocity and position of the ith particle, w is inertia weight that introduces the weighting of the current velocity on the particle in the next generation, p_{id}^k represents the position with the best fitness found so far by the ith particle, usually called *pbest*, p_{gd}^k is the position with the best fitness found so far by all the particles in the population, usually called *gbest*, c_1 and c_2 are two positive constants called acceleration coefficients, r_1 and r_2 are two random numbers distributed in (0,1). In the searching process, all the particles cooperate with each other, and finally achieve the optimal solution while the fitness function is optimized.

The main procedure of PSO is described as follows:

Step 1: Initialize all the particles (velocity and position) randomly, evaluate the fitness of each particle in the population, and get *pbest* and *gbest*.
Step 2: Stop the algorithm if the stopping criterion is satisfied, otherwise go to Step 3.
Step 3: Update the velocity and position of each particle according to Eqs. (1) and (2), and evaluate the fitness of each particle, update *pbest* and *gbest*.
Step 4: Return to Step 2.

Because of its simple concept and iterative operations, PSO has become a popular optimization method and has been widely used in practical problem solving. Meanwhile, many scholars have done lots of theoretical studies and improvements on the algorithm. Clerc and Kennedy [36] used a five-dimensional depiction to describe and analyze a particle's trajectory as it moves, containing a set of coefficients to control the system's convergence tendencies. Shi and Eberhart [37] introduced the parameter, called inertia weight, into the original particle swarm optimization, and proposed a strategy of varying the value of inertia weight from 0.9 to 0.4 to improve the performance [38]. Ratnaweera et al. [39] introduced a novel parameter automation strategy of time-varying acceleration coefficients in PSO, which efficiently controls the local search and convergence to the global optimum solution. Zhan et al. [14] presented an adaptive particle swarm optimization that enables the automatic control of inertia weight, acceleration coefficients, and other algorithmic parameters at run time by evaluating the population distribution and particle fitness to improve the search efficiency and convergence speed. Except the parameter studies mentioned above, many scholars have tried to combine PSO with other concepts to improve the performance. B. Alatas et al. [40] proposed chaos embedded particle swarm optimization algorithm using chaotic maps for parameter adaptation. Bergh Engelbrecht [41] employed cooperative behavior to significantly improve the performance of PSO, and presented a variation called cooperative particle swarm optimizer (CPSO). In CPSO, multiple swarms are used to optimize different components of the solution vector cooperatively, and the performance is markedly improved.

2.2. Cultural algorithm (CA)

Cultural algorithms can be described in terms of two basic components: belief space and population space [42]. Fig. 1 presents the framework of cultural algorithm. The belief space can be

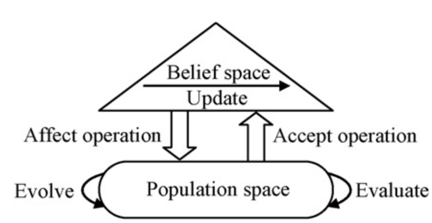

Fig. 1. Framework of cultural algorithm.

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