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Enhancing the performance of biogeography-based optimization using polyphyletic migration operator and orthogonal learning

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ABSTRACT

Biogeography-based optimization (BBO) is a powerful population-based algorithm inspired by biogeography and has been extensively applied to many science and engineering problems. However, its direct-copying-based migration and random mutation operators make BBO possess local exploitation ability but lack global exploration ability. To remedy the defect and enhance the performance of BBO, an enhanced BBO variant, called POLBBO, is developed in this paper. In POLBBO, a proposed efficient operator named polyphyletic migration operator can formally utilize as many as four individuals' features to construct a new solution vector. This operator cannot only generate new features from more promising areas in the search space, but also effectively increase the population diversity. On the other hand, an orthogonal learning (OL) strategy based on orthogonal experimental design is employed. The OL strategy can quickly discover more useful information from the search experiences and efficiently utilize the information to construct a more promising solution, and thereby provide a systematic and elaborate reasoning method to guide the search directions of POLBBO. The proposed POLBBO is verified on a set of 24 benchmark functions with diverse complexities, and is compared with the basic BBO, five state-of-the-art BBO variants, five existing OL-based algorithms, and nine other evolutionary algorithms. The experimental results and comparisons demonstrate that the polyphyletic migration operator and the OL strategy can work together well and enhance the performance of BBO significantly in terms of the quality of the final solutions and the convergence rate.

1. Introduction

Optimization problems are of increasing importance in modern science and engineering fields. They turn to be more complicated and diversified commensurate with the unceasing progress of science and technology. Different undesirable but unavoidable features such as noisy, high-dimensional, non-differentiable, non-continuous, and non-convex pose daunting challenges for solutions. In this context, evolutionary algorithms (EAs), over the last few decades, have received much attention [1] and demonstrated their effectiveness as powerful optimizers for difficult, nonlinear, multimodal optimization problems [2]. Some popular EAs include genetic algorithm [3–5], differential evolution (DE) [6,7], particle swarm optimization [8–10], ant colony optimization [11,12], artificial bee colony [13–15], etc.

Biogeography-based optimization (BBO) [16] is a novel, recently developed EA based on the equilibrium theory of island biogeography. Biogeography is the science and study of the geographical distribution of biological organisms. The mathematical models of biogeography describe how species migrate from one island to another, how new species arise, and how species become extinct. Motivated by this theory, BBO operates by probabilistically sharing information between individuals in a population of candidate solutions just like species migrate back and forth between islands. BBO has certain features in common with other EAs, such as sharing information between solutions, admittedly. On the other hand, it has its own distinctive features. One is that BBO uses individuals' fitness values to calculate their immigration and emigration rates for each generation, making poor individuals have a high probability of accepting new features from good individuals to improve their quality. Since its invention in 2008, BBO has shown good performance on benchmark functions [17–19] and been successfully applied to a variety of real-world problems [20–24].

However, similar to other EAs, BBO has also been shown to have certain weaknesses. Although its convergence speed is relatively fast at the beginning of the evolutionary process, it easily falls into local optima and suffers from premature convergence thereafter. The main reason behind the phenomenon is as follows. For a population-based EA, it is well known that both exploration (i.e. the global search) and exploitation (i.e. the local search) are indispensable. Excessive emphasis on exploitation would give rise to pure local search, whereas excessive emphasis

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on exploration would lead to pure random search. For BBO, its probabilistic migration can make the population share information among solutions and thus enable BBO to possess good exploitation ability [25]. However, its direct-copying-based migration and random mutation operators make BBO lack enough exploration ability, resulting in the scarcity of population diversity.

To remedy the defect mentioned above, much effort has been made and a number of BBO variants have been proposed. One research hotspot focuses on its migration operator. The motivation is that the basic migration operator of BBO shown in (3) in Section 2 simply provides reproduction of new solutions through copying features from a constant pool and cannot generate new features from more promising areas in the search space. Up to now, some migration operators have been developed. For example, Li et al. [26] proposed a perturb migration operator to produce a perturbation from a neighbor to update the target individual. Li and Yin [27] employed a multi-parent crossover based migration operator by which three consecutive individuals can generate three offspring according to their fitness values. Ma and Simon [28] presented a blended migration operator which can make two parents contribute different constant weighted features to a new feature of an offspring. Aiming at the constant weights, Sayed et al. [29] utilized a strategy based on the two parents' fitness ranks in the current population to adaptively adjust them. From the experimental results of [26–29], it can be seen that a well-designed migration operator indeed contributes to improving the performance of BBO.

Besides designing effective migration operator, another possible improvement of BBO is hybridization with other operators or algorithms. The main motivation is to take advantage of the exploration abilities of other operators or algorithms to increase the population diversity of BBO and thus prevent it from being dropped into local optima. For example, both [26] and [27] integrated Gaussian mutation into BBO to increase the population diversity. Gong et al. [30] embedded Gaussian, Cauchy, and Lévy mutations, respectively, into BBO. Ergezer et al. [31] adopted opposition-based learning alongside BBO's migration rates to accelerate its performance. Boussaïd et al. [32] combined BBO with DE to update the population alternately, and adopted a selection procedure to favor the fitter individuals for the next generation. Gong et al. [25] hybridized the BBO migration operator with the DE mutation operator to generate a new hybrid migration operator for BBO and also used a selection operator to preserve the fitter individuals. Yang et al. [33] employed opposition-based learning and chaotic maps to initialize the population of BBO, and incorporated Gaussian distribution as its mutation operator. Wang and Xu [34] utilized the DE mutation operator and the simplex operator, respectively, to speed up the searching progress and enhance the searching accuracy of BBO.

In this paper, we concentrate on both migration operator and hybridization. On one hand, an effective migration operator called polyphyletic migration operator is proposed. This operator is able to formally use as many as four individuals' features to construct a new solution vector. It can not only generate new features from new promising areas in the search space, but also effectively increase the population diversity. On the other hand, it is undeniable that good solutions may have relatively poor values on some dimensions while poor solutions may possess promising values on some other dimensions. In this context, directly abandoning poor solutions may result in missing these promising values. Intrinsically, the basic migration operator of BBO and those modified migration operators mentioned above are much like a generate-and-go operator that blindly searches in a randomly selected dimension of a solution and thus cannot make the best use of the search experiences. Therefore, how quickly to discover more useful information from the search experiences and effectively utilize the information to construct more promising solutions are significantly important and essential. To this end, orthogonal experimental design (OED) may be one of the best tools. OED is able to offer an ability to discover the best combination levels for different factors with a reasonably small number of experimental samples [35]. Hence, in this paper, the OED is employed to form an orthogonal learning (OL) strategy for BBO. The OL strategy is able to efficiently generate a good candidate solution for the next generation by using a systematic and elaborate reasoning method instead of the generate-and-go method and thereby guide the search directions toward the global optimum. The proposed algorithm, referred to as POLBBO which combines the polyphyletic migration operator and the OL strategy, is verified on 24 benchmark functions with diverse complexities.

The remainder of this paper is organized as follows. Section 2 briefly introduces the basic BBO. The proposed algorithm, POLBBO, is elaborated in Section 3. In Section 4, comprehensive experimental tests are conducted on 24 benchmark functions to verify POLBBO. Finally, Section 5 is devoted to conclusions and future work.

2. Biogeography-based optimization (BBO)

The BBO algorithm, which is strongly inspired by the equilibrium theory of island biogeography, is a population-based algorithm developed for the global optimization. In BBO, each individual is called a "habitat" and has a habitat suitability index (HSI) instead of fitness value to measure the goodness. The variables of a habitat that characterize habitability are composed of a D-dimensional real vector and are called suitability index variables (SIVs). A good solution tends to have a large number of species and it is analogous to an island with a high HSI, and vice versa. Solution features immigrate to low HSI solutions from high HSI solutions to raise the quality of poor solutions. Namely, good solutions tend to share their features with poor solutions, and poor solutions accept a lot of new features from good solutions.

In BBO, the immigration rate λ and emigration rate μ of each habitat are functions of the number of species in the habitat and are used to share information between habitats. They can be calculated using sinusoidal migration model [17] as follows:

$$\lambda_i = \frac{I}{2}\left(\cos\left(\frac{\pi S_i}{S_{\max}}\right) + 1\right) \tag{1}$$

$$\mu_i = \frac{E}{2}\left(-\cos\left(\frac{\pi S_i}{S_{\max}}\right) + 1\right) \tag{2}$$

BBO contains two basic operators, i.e., migration and mutation. The migration operator is used to modify the selected habitat's SIV by sharing features between habitats. Migration can be expressed as

$$H_i(\text{SIV}) \leftarrow H_e(\text{SIV}) \tag{3}$$

where H_i is an immigrating habitat and H_e is an emigrating habitat. Migration operator can be informally described in Algorithm 1, where NP denotes the number of habitats. rand(0, 1) is a uniformly distributed random real number in (0, 1).

Algorithm 1. Migration operator.

```
for i = 1 to NP do
  Select habitat H_i with respect to rate λ_i
  if rand(0, 1) < λ_i then
    for e = 1 to NP do
      Select habitat H_e with respect to rate μ_e
      Randomly select a SIV from H_e
      Perform (3) on H_i
    end for
  end if
end for
```