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Biogeography-based optimization with covariance matrix based migration

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ABSTRACT

Biogeography-based optimization (BBO) is a new evolutionary algorithm. The major problem of basic BBO is that its migration operator is rotationally variant, which leaves BBO performing poorly in non-separable problems. To overcome this drawback of BBO, in this paper, we propose the covariance matrix based migration (CMM) to relieve BBO's dependence upon the coordinate system so that BBO's rotational invariance is enhanced. By embedding the CMM into BBO, we put forward a new BBO approach, namely biogeography-based optimization with covariance matrix based migration, called CMM-BBO. Specifically, CMM-BBO algorithms are developed by the CMM operator being randomly combined with the original migration in various existing BBO variants. Numeric simulations on 37 benchmark functions show that our CMM-BBO approach effectively improves the performance of the existing BBO algorithms.

1. Introduction

Inspired from the nature, a variety of evolutionary algorithms (EAs) has been developed to effectively tackle global optimization problems, for example, genetic algorithms (GA) [1], evolution strategies (ES) [2], differential evolution (DE) [3–5], particle swarm optimization (PSO) [6,7] and so on. EAs have the advantages such as robustness, reliability, global search capability and little or no prior knowledge required.

Biogeography-based optimization (BBO), proposed by Simon [8], is a new EA based on biogeographic evolution. BBO has proven itself a competitive heuristic to other EAs on a wide range of problems [8–12].

To improve the performance of basic BBO, a number of BBO variants have been proposed, which generally fall into three categories, i.e., (i) BBO with new migration or mutation operators, (ii) BBO hybrid with other EAs, and (iii) BBO with multiple populations or local topologies.

BBO with new migration or mutation operators: Gong et al. [13] proposed a real-coded BBO (called rcBBO) with three kinds of mutation operators, namely Gaussian mutation, Cauchy mutation, and Lévy mutation. Li and Yin [14] proposed a multi-operator BBO (called moBBO) with generalized migration operator using multi-parent migration model. Xiong et al. [15] proposed a BBO with polyphyletic migration operator and orthogonal learning strategy, called polBBO. Li et al. [16] proposed a perturbation optimization based BBO (called pBBO) with perturbation migration operator using sinusoidal migration model. Ma and Simon [17] proposed a blended BBO, for constrained optimization, with blended migration operator by analogue to the blended crossover operator in GA. Simon et al. [18] proposed a BBO with linearized migration that makes the migration more rotationally invariant.

BBO hybrid with other EAs: Du et al. [19] incorporated the elitism mechanism of evolutionary strategy and a new immigration refusal scheme into BBO and proposed a BBO/ES/RE algorithm. Gong et al. [20] incorporated DE's mutation operator with BBO's migration operator and proposed a DE/BBO algorithm, taking advantage of BBO's exploitation ability and DE's exploration ability. Boussaid et al. [21] incorporated DE with BBO through a two-stage updating mechanism and proposed

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a DE hybrid BBO algorithm. Kundra and Sood [22] combined PSO with BBO to optimize shortest path problems. Savsani et al. [23] incoprporated artificial immune algorithm and ant colony optimization with BBO and proposed four hybrid BBO variants.

BBO with multiple populations or local topologies: Zheng et al. [24] integrated three different local topologies (i.e., ring, square, and random) in BBO to enhance BBO's exploration ability, and proposed a localized BBO. Zheng et al. [25] divided the whole population into multiple sub-populations with each sub-population being evolved through a separate BBO, and proposed a cooperative coevolutionary biogeography-based optimizer (called cBBO). Ma et al. [26] proposed a BBO with an ensemble of migration models using three parallel populations, each implementing a different migration model.

In addition to the three categories of BBO variants above, Ergeze et al. [27] proposed an oppositional BBO using opposition-based learning. Saremi et al. [28] proposed a chaotic BBO using ten chaotic maps to define selection, emigration, and mutation probabilities.

In BBO algorithms as mentioned above, either basic BBO or variants, the migration operator is crucial. In fact, it is through the migration operator that multiple parents contribute towards generating an offspring. However, the migration operators in the existing BBO algorithms are heavily dependent upon the coordinate systems, which leaves poor performance in dealing with non-separable problems [18]. A non-separable problem is one the fitness of which depends upon the variables combinatorially rather than individually. In other words, variables in a non-separable problem are tightly intermeshed with one another.

Simon et al. pointed out [18] that a major drawback of BBO is that it treats each solution feature independently, which leaves BBO rotationally variant. Rotational variance means that BBO generally performs poorly when applied to non-separable problems. However, most real-world problems are non-separable. Thus, rotational variance restricts BBO's applicability to wider problems.

To address this drawback of BBO, the key question is: how to relieve BBO's dependence upon the coordinate system and enhance BBO's rotational invariance?

Covariance matrix learning (CML) was first adopted in covariance matrix adaptation evolution strategy (CMAES) [2]. CML effectively adapts the search according to the landscape of the optimization function. Basically, CML rotates the coordinate system to make the problem pseudo-separable. CML employed in DE makes the crossover rotationally invariant [29,30], which significantly improves the performance of DE.

In this paper we will propose the covariance matrix based migration (CMM) to relieve BBO's dependence upon the coordinate system so that BBO's rotational invariance is enhanced. By use of our proposed CMM operator, the original coordinate system is rotated into an eigenvectorbased one, in which solutions can share their information more efficiently.

By embedding the CMM into BBO, we put forward a new BBO approach, namely biogeography-based optimization with covariance matrix based migration, called CMM-BBO. Specifically, CMM-BBO algorithms are developed by the CMM operator being randomly combined with the original migration in various exsiting BBO algorithms.

The remainder of the paper is arranged as follows. Section 2 proposes the covariance matrix based migration and puts forward the CMM-BBO approach. Section 3 conducts thorough performance evaluations of four CMM-BBO algorithms through numeric simulations on 37 benchmark functions and comparisons with other EAs. Lastly, Section 4 draws the conclusions.

2. BBO with covariance matrix based migration

2.1. Preliminary: basic BBO

BBO [8] is a new population-based, biogeographically inspired global optimization algorithm. In BBO, each individual is regarded as a "habitat" or "island" with a Habitat Suitability Index (HSI), which is similar to the fitness in EAs. A good solution means a habitat with a high HSI, while a poor solution indicates a habitat with a low HSI.

A solution can be represented by a set of Suitability Index Variables (SIV). In BBO's migration process, high HSI solutions should share their features with low HSI ones; while low HIS solutions take in new features from high HIS ones. In BBO, each individual has its own immigration rate λ and emigration rate μ, which can be calculated based on HSI. A high HSI habitat has a high species emigration rate μ while a low HSI habitat has a high species immigration rate λ. For example, in a linear model of species richness, a habitat H_i's immigration rate λ_i and emigration rate μ_i can be calculated as follows.

$$\lambda_i = I\left(1 - \frac{i}{n}\right) \tag{1}$$

$$\mu_i = E\left(\frac{i}{n}\right) \tag{2}$$

where I is the maximum immigration rate, E the maximum emigration rate, n the population size, i the index of the individual in order, where $i = 1$ denoting the worst individual while $i = n$ denoting the best. Eqs. (1) and (2) are called linear migration model of the migration rates.

Migration modifies habitats by mixing the features within a population. BBO also uses a mutation operator to change the SIV of a habitat itself, and thus increases the diversity of a population. For each habitat H_i, species count probability P_i, computed from λ_i and μ_i, measures the *a priori* likelihood that the habitat is expected to become a solution to the problem. In reality, either a very high HSI habitat or a very low HSI habitat is rarely probable, but most probable is a medium HSI habitat. A habitat's mutation rate π_i is inversely proportional to its probability, i.e.,

$$\pi_i = \pi_{\max}\left(1 - \frac{P_i}{P_{\max}}\right) \tag{3}$$

where $\pi_{\max}$ is a control parameter and $P_{\max}$ the maximum habitat probability in a population.

Basic BBO can be formulated as in Algorithm 1, where D is the dimension of the optimization problem, l_d and u_d the lower and upper bounds of the d-th dimension, respectively, and rand a random number function uniformly distributed in [0,1].

Algorithm 1. Basic BBO