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Linearized biogeography-based optimization with re-initialization and local search

Dan Simon [a,*], Mahamed G.H. Omran [b], Maurice Clerc [c]

[a] Department of Electrical and Computer Engineering, Cleveland State University, Cleveland, OH, United States
[b] Department of Computer Science, Gulf University for Science and Technology, Kuwait
[c] 204, route de la Nerulaz, 74570 Groisy, France

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ABSTRACT

Biogeography-based optimization (BBO) is an evolutionary optimization algorithm that uses migration to share information among candidate solutions. One limitation of BBO is that it changes only one independent variable at a time in each candidate solution. In this paper, a linearized version of BBO, called LBBO, is proposed to reduce rotational variance. The proposed method is combined with periodic re-initialization and local search operators to obtain an algorithm for global optimization in a continuous search space. Experiments have been conducted on 45 benchmarks from the 2005 and 2011 Congress on Evolutionary Computation, and LBBO performance is compared with the results published in those conferences. The results show that LBBO provides competitive performance with state-of-the-art evolutionary algorithms. In particular, LBBO performs particularly well for certain types of multimodal problems, including high-dimensional real-world problems. Also, LBBO is insensitive to whether or not the solution lies on the search domain boundary, in a wide or narrow basin, and within or outside the initialization domain.

1. Introduction

Evolutionary algorithms (EAs) have demonstrated their effectiveness over the last few decades as powerful optimizers for difficult, nonlinear, multimodal optimization problems [17]. EAs are generally, but not always, based on some natural process. Some popular EAs include particle swarm optimization (PSO) [27], differential evolution (DE) [65], ant colony optimization (ACO) [15], and genetic algorithms (GAs) [22]. EAs generally involve a collection of candidate solutions to some optimization problem. These candidate solutions are often called individuals, or simply solutions, and the collection of all the candidate solutions is called the population. Candidate solutions combine with each other and are also subject to random changes. The merging of candidate solutions is called recombination, and results in new candidate solutions. Random changes to candidate solutions are called mutations. Recombination and mutation create new solutions, and the EA thus progresses from one generation to the next in an attempt to find ever-improving solutions to a given problem.

One recently-developed EA is biogeography-based optimization (BBO), which, as its name indicates, is motivated by the mathematics of biogeography. Biogeography is the science and study of the migration of plant and animal life between habitats. Alfred Wallace and Charles Darwin were famous naturalists in the 19th century who conducted initial research in biogeography and introduced the subject to the scientific community [50]. Biogeography grew from a qualitative study to a

* Corresponding author. Tel.: +1 216 687 5407.
E-mail addresses: d.j.simon@csuohio.edu (D. Simon), omran.m@gust.edu.kw (M.G.H. Omran), maurice.clerc@writeme.com (M. Clerc).

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quantitative study with the doctoral dissertation of Eugene Monroe in 1948 [11], and with a popular book authored by Robert MacArthur and Edward Wilson [40].

Biogeography motivated the development of biogeography-based optimization in 2008 [61]. Since then, BBO has been mathematically modeled as a Markov process [64] and as a dynamic system [62]. BBO has been successfully applied to many real-world problems, including robot control tuning [36], power system optimization [54], mechanical gear train design [57], satellite image classification [47], antenna design [59], image processing [51], prosthesis control optimization [69], and neuro-fuzzy system training for biomedical applications [46].

BBO has seen several improvements since it was first introduced. Ma and Simon [37] explored various migration curve shapes, which affect the selection pressure used for recombination. They also added blending to the BBO recombination logic, which resulted in the linear combination of independent variables during recombination [38]. Several researchers have hybridized BBO with other EAs, including DE [10], PSO [29], and oppositional learning [20].

However, in spite of these and other improvements, BBO still changes only one independent variable at a time in its candidate solutions. This is explained in more detail in Section 2, but the important point to note here is that this single-feature-migration property of BBO can result in poor performance on nonseparable problems. A nonseparable problem is one whose fitness depends on combinations of variables, rather than on individual variables. Many real-world problems are nonseparable and so this shortcoming of BBO must be addressed to make it more applicable. In this paper we modify BBO to obtain an algorithm called linearized BBO (LBBO) that is intended to improve BBO's performance, especially on nonseparable problems.

Section 2 gives an overview of standard BBO. Section 3 extends the BBO algorithm to LBBO and augments with the algorithm with several additional features, including local search and re-initialization. Section 4 discusses our experimental setup for the evaluation of LBBO and compares it with other state-of-the-art EAs. Section 5 presents a sensitivity study of the contributions of the various components of LBBO, and especially shows the importance of gradient descent (local search). Section 6 provides some concluding comments and suggestions for further research.

2. Biogeography-Based Optimization (BBO)

BBO is a population-based optimization method where each candidate solution is called a *habitat*. Each habitat has a habitat suitability index (HSI), which corresponds to the fitness of a solution. A good solution is like a habitat with a high HSI (a habitat with large number of species) while a bad solution is like a habitat with a small HSI (a habitat with small number of species). Good solutions tend to share their features with other solutions, while bad solutions are more likely to accept features from other solutions. This principle is motivated by natural biogeography, where high-population islands are more likely to emigrate species, and low-population islands are more likely to immigrate species [40]. Each solution y_k in BBO has two parameters, the immigration rate λ_k and emigration rate μ_k, where λ_k is inversely proportional to the fitness of y_k while μ_k is proportional to the fitness of y_k. Both λ_k and μ_k are defined on the domain [0, 1]. Thus, good solutions have low λ and high μ, while bad solutions have high λ and low μ. BBO consists of two main steps: migration and mutation.

2.1. Migration, or information sharing

For each solution feature $y_{k,s}$, the immigration rate λ_k is used to probabilistically decide whether or not to immigrate to that solution feature. This is described in Algorithm 1.

Algorithm 1. BBO migration decision. y_k is the kth candidate solution. r is a random number taken from a uniform distribution on $(0,1)$. $\lambda_k \in [0,1]$ is the immigration rate and is described in Eq. (3). $y_{k,s}$ is the sth solution feature (that is, the sth independent variable) of $y_{k,s}$.

```
r ~ U(0,1)
If r < λ_k then
  Immigrate to y_k,s
else
  Do not immigrate to y_k,s
End if
```

Note that Algorithm 1 is performed for each solution feature index $s \in [1,n]$, where n is the problem dimension. If a decision is made by Algorithm 1 to immigrate to $y_{k,s}$, then the emigrating solution y_j is chosen probabilistically (e.g., using roulette wheel selection) using the emigration rates of the entire population:

$$\text{Prob(emigration from } y_j) = \frac{\mu_j}{\sum_{m=1}^{N}\mu_m} \quad \text{for all } j \in [1,N] \tag{1}$$