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Biogeography-Based Optimization with Blended Migration for Constrained Optimization Problems

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ABSTRACT
Biogeography-based optimization (BBO) is a new evolutionary algorithm based on the science of biogeography. We propose two extensions to BBO. First, we propose blended migration. Second, we modify BBO to solve constrained optimization problems. The constrained BBO algorithm is compared with solutions based on a genetic algorithm (GA) and particle swarm optimization (PSO). Numerical results indicate that BBO generally performs better than GA and PSO in handling constrained single-objective optimization problems.

Categories and Subject Descriptors: G.1.6 [Numerical Analysis]: Optimization – constrained optimization; stochastic programming.

General Terms: Algorithms.

Keywords: evolutionary algorithm, biogeography-based optimization, constrained optimization.

1. INTRODUCTION
Many optimization problems in science and engineering have constraints. Evolutionary algorithms (EAs) have been successful for a wide range of constrained optimization problems [8]. Biogeography-based optimization (BBO) is a new evolutionary algorithm for global optimization that was introduced in 2008 [11]. It is modeled after the migration of species between habitats. One key feature of BBO is that the original population is not discarded after each generation. It is rather modified by migration. Another key feature is that BBO uses the fitness of each solution to determine its migration rates. BBO has demonstrated good performance on unconstrained benchmark functions [11]. It has also been applied to real-world optimization problems such as sensor selection [11], power system optimization [10], groundwater detection [4], and satellite image classification [9].

We propose two extensions to BBO. First, we use the blended crossover operator of the GA [6] to derive a blended migration operator for BBO. Second, we generalize BBO to constrained optimization problems. We adapt a method for constrained optimization which emphasizes the distinction between feasible and infeasible solutions in the search space [1], [3].

2. BLENDED BBO
In BBO, there are two main operators: migration and mutation. We propose a new migration operator called blended migration, which is a generalization of the standard BBO migration operator, and which is motivated by blended crossover in GAs [6]. Blended migration is defined as

\[ H_I(s) \leftarrow \alpha H_I(s) + (1-\alpha) H_J(s) \]  

for each solution \( H_i \)

For each solution feature \( s \)

Select solution \( H_i \) with probability \( \propto (1 - \text{fitness}_i) \)

If \( H_i \) is selected then

Select solution \( H_j \) with probability \( \propto \text{fitness}_j \)

If \( H_j \) is selected then

\[ H_s(s) \leftarrow \alpha H_I(s) + (1-\alpha) H_J(s) \]

end

Probabilistically mutate \( H_i \)

next solution feature

next solution

Figure 1. BBO Algorithm with fitness is normalized to \([0, 1]\).

\( \alpha = 0 \) for standard BBO, and \( \alpha > 0 \) for blended BBO.

3. CONSTRAINED OPTIMIZATION
In this paper we incorporate a method into BBO for constraint-handling based on feasibility rules which have demonstrated promising performance [1], [3]. Note from Figure 1 that the migration procedure modifies each solution to create a new solution. For constrained BBO, we check each solution to see if it is better than its version before migration. The new solution will replace its previous version only if it is better than its previous version. This is similar to a (\( \mu+\lambda \)) evolutionary strategy where the next generation is chosen from both parents and children [2].

For constrained problems, when a solution \( H_1 \) is compared to a solution \( H_2 \), solution \( H_1 \) is considered better if and only if:

1) Both solutions are feasible, but \( H_1 \) has a cost that is less than or equal to that of \( H_2 \); or,

2) \( H_1 \) is feasible and \( H_2 \) is not; or,

3) Both solutions are infeasible, but \( H_1 \) has a smaller overall constraint violation.
4. SIMULATION RESULTS
We used a representative set of constrained benchmark functions to test the proposed approach [5], [7]. Simulation parameters were:
1) Population size: 50
2) Number of features per solution (problem dimension): 20
3) Mutation probability: 5% per solution feature
4) Number of elite solutions per generation: 2
5) Maximum number of fitness function evaluations: 10,000
6) Number of Monte Carlo simulations per experiment: 30

Number of successes (NS) represents the number of simulations for which \( f(x) - f_{\text{opt}} \leq 0.0001 \) with feasible \( x \), where \( f_{\text{opt}} \) is the best known solution from [7]. We compare BBO, Blended BBO, GA, and PSO. The proposed constraint-handling method is adapted in an identical way for all four algorithms. Table 1 shows the results of solving the constrained benchmark functions. BBO outperforms GA and PSO on 8 of 13 benchmarks, and Blended BBO outperforms BBO on 10 of 13 benchmarks. This includes not only mean results and number of successes, but also standard deviation, which implies that BBO and blended BBO are more robust than GA and PSO.

We conclude that: (1) BBO is a competitive algorithm for solving constrained optimization problems; (2) constrained BBO outperforms GAs and PSO for the benchmark problems in this paper; and (3) Blended migration outperforms BBO.

Table 1. Results obtained on constrained benchmark problems: the mean solution found over 30 Monte Carlo simulations, the standard deviation of the 30 solutions, and the number of successes (NS). The best results are shown in red boldface.

<table>
<thead>
<tr>
<th>Fn.</th>
<th>BBO</th>
<th>GA</th>
<th>PSO</th>
<th>Blended BBO</th>
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<td></td>
<td>Mean</td>
<td>Std Dev</td>
<td>NS</td>
<td>Mean</td>
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<tr>
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6. REFERENCES

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