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Biogeography-Based Optimization with Blended Migration for Constrained Optimization Problems

Haiping Ma
Shaoxing University, Shaoxing, China, mahp@usx.edu.cn

Daniel J. Simon
Cleveland State University, d.j.simon@csuohio.edu

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Haiping Ma
Shaoxing University
Shaoxing, Zhejiang, 312000, China
mahp@usx.edu.cn

Dan Simon
Cleveland State University
Cleveland, Ohio
d.j.simon@csuohio.edu

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

$$H_i(s) \leftarrow \alpha H_i(s) + (1-\alpha) H_j(s) \tag{1}$$

where H_i is the ith candidate solution in the BBO population, s is its solution feature, and α is a real number between 0 and 1. Equation (1) means that a solution feature of solution H_i is not simply replaced by a feature from solution H_j. Instead, a new feature in a BBO solution is comprised of two components: the migration of a feature from another solution, and the migration of a feature from itself. The BBO algorithm, generalized for blended migration, is shown in Figure 1.

```
For each solution Hi
  For each solution feature s
    Select solution Hi with probability ∝ (1 − fitness_i)
    If Hi is selected then
      Select Hj with probability ∝ fitness_j
      If Hj is selected then
        Hi(s) ← αHi(s) + (1−α)Hj(s)
      end
    end
    Probabilistically mutate Hi
  next solution feature
next solution
```

Figure 1. BBO Algorithm with fitness is normalized to [0, 1]. α = 0 for standard BBO, and α > 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 (μ+λ) 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 $f(x) - f_{\min} \le 0.0001$ with feasible x, where $f_{\min}$ 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.

Fn.	BBO			GA			PSO			Blended BBO		
	Mean	Std Dev	NS	Mean	Std Dev	NS	Mean	Std Dev	NS	Mean	Std Dev	NS
g01	1.1E–03	4.7E–04	20	3.5E–02	8.4E–03	15	2.9E–03	4.4E–03	15	**2.7E–05**	**9.0E–06**	**30**
g02	**0.00**	**0.00**	**30**	1.3E–01	6.6E–01	10	1.1E–02	4.9E–02	14	**0.00**	**0.00**	**30**
g03	3.3E–02	8.3E–03	12	2.7E–01	7.9E–02	10	2.8E–02	6.0E–04	12	**3.1E-05**	**9.2E-05**	**30**
g04	1.3E+01	9.4E+00	0	3.0E+02	1.8E+02	0	3.9E+01	3.5E+01	0	**2.5E+00**	**3.2E+00**	**2**
g05	5.5E–08	5.9E–07	22	5.0E–06	5.7E–05	18	2.4E–01	1.1E–01	4	**8.5E-09**	**9.0E–09**	**30**
g06	3.0E–01	4.1E–01	16	9.0E+01	8.7E+00	6	2.1E–01	**5.9E–02**	**18**	**1.4E–01**	5.2E-01	16
g07	2.2E+00	7.6E–01	3	8.5E+00	6.4E+00	2	9.0E+00	7.9E+00	2	**3.5E–01**	**1.5E–01**	**8**
g08	5.8E–11	4.4E–12	**30**	**1.0E–12**	**2.6E–13**	**30**	7.5E–08	9.0E–08	**30**	7.2E-12	2.6E-12	**30**
g09	**0.00**	**0.00**	**30**	3.1E+00	2.2E+00	3	1.7E+00	6.9E+00	10	**0.00**	**0.00**	**30**
g10	7.4E+01	9.0E+00	**5**	9.2E+00	2.4E+00	3	**3.9E+00**	**1.9E+00**	**5**	5.5E+01	**1.9E+00**	1
g11	**0.00**	**0.00**	**30**	**0.00**	**0.00**	**30**	1.3E–03	3.5E–03	15	**0.00**	**0.00**	**30**
g12	3.8E–07	6.1E–08	**30**	1.4E–05	5.4E–06	15	7.8E–05	9.9E–06	22	**8.5E–08**	**1.5E–08**	**30**
g13	2.9E–01	**2.4E–02**	7	9.2E+00	1.0E–01	7	1.8E+00	8.4E–01	7	**5.7E–02**	3.2E–02	**10**

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