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Heuristic Crossover Based on Biogeography-based Optimization

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Abstract. Biogeography based optimization (BBO) is a new evolutionary optimization algorithm based on the science of biogeography for global optimization. In this paper, we proposed two extensions to BBO. First, we proposed a new migration operation based sinusoidal migration model with the heuristic crossover operator. We have presented three heuristic crossover operators, they are constant heuristic crossover operator, random heuristic crossover operator and dynamic heuristic crossover operator. Among them, the migration operation used random heuristic crossover operator (HCBBO) is optimal. Then, as we all know, the Gaussian mutation operator is optimal to settle unimodal function, the random mutation operator is optimal to settle multimodal function. Therefore, we have presented a stable mixture mutation approach based on an improved variant of BBO, it is a biogeography of hybrid with random mutation and Gauss mutation based optimization algorithm using sinusoidal migration model. Experiments have been conducted on 14 benchmark problems of a wide range of dimensions and diverse complexities. Simulation results and comparisons demonstrate the proposed HCBBO algorithm using sinusoidal migration model surpasses other improved BBO, the mixture BBO is stability than other algorithms from literatures in recent years when considering the quality of the solutions obtained.

Introduction

Biogeography based optimization (BBO) is a new evolutionary algorithm for global optimization that was invented in 2008 by Dan Simon [1], while attempting to simulate the colonization and extinction of species between habitats. This new population-based stochastic optimization technique is based on the mathematical models of the natural phenomenon of biogeography. In this algorithm, each habitat represents a candidate solution for the optimization problem and gets modified by the process of migration. The colonization and extinction rates are calculated with reference to the fitness of each solution. Originally, the BBO algorithm was proposed for optimization problems, where several modifications have been proposed such as [2-6] .However, The performances of the proposed algorithms are better.

Biogeography Based Optimization with Heuristic Crossover

Migration Model. BBO is a new population-based biogeography inspired global optimization algorithm[7-10], which gives it certain features in common with other EAs. In BBO, each real number in the array is considered as a SIV. The goodness of each solution is called as its habitat suitability index (HIS) which is analogous to ‘‘fitness’’ in other population-based optimization algorithm. In BBO, each individual has its own immigration rate λ and emigration rate μ. The immigration rate and emigration rate are functions of the number of species in the habitat. They can be calculated as follows:

$$\lambda_i = I(1-\frac{i}{N}) \tag{1}$$

$$\mu_i = E(\frac{i}{N}) \tag{2}$$

where I is the maximum possible immigration rate, E is the maximum possible emigration rate, i is the number of species of the ith individual, and n is the maximum number of species. As we can see, this model is a linear migration model. However, the process of migration is more complicated than a linear curve because the ecosystem is inherently nonlinear, where simple changes in one part of the system will produce complex effects throughout the entire system. In this sense, linear model is too simple to explain the complicated problem such as migration. The immigration rate and emigration rate are functions of the number of species in the habitat. They can be calculated as follows:

$$\lambda_i = \frac{I}{2}(1+\cos(\frac{i\pi}{N})) \tag{3}$$

$$\mu_i = \frac{E}{2}(1-\cos(\frac{i\pi}{N})) \tag{4}$$

In BBO, migration denotes the movement species among different habitats. The migration strategy is similar to the evolutionary strategy in which many parents can contribute to a single offspring. BBO migration is used to change existing solution and modify existing island. Migration is a probabilistic operator that adjusts a habitat Hi. The probability Hi is modified proportional to its immigration rate λi, and the source of the modified probability comes from Hj is proportional to the emigration rate μj. Migration can be described as follows:

$$H_i(SIV) \leftarrow H_j(SIV) \tag{5}$$

In this paper, we propose a new migration operation based sinusoidal migration model, called perturb migration, which is a generalization of the standard BBO migration operator. In perturb migration model, instead of copying a parent’s island if the Hi is not chosen with the probability proportional to λi, we use the operator of perturb method from the neighborhood island to update the Hi, which is described as follows:

Model 1 Constant heuristic crossover model:

Hi (SIV)= Hi (SIV)+0.12(Hi (SIV) –Hr(SIV)) (6)

where r is a random individual, $r = \lfloor N \cdot rand(0,1) \rfloor$.

Model 2 Randomly heuristic crossover model:

Hi (SIV)= Hi (SIV)+(0.5-rand(0,1))(Hi (SIV) –Hr(SIV))
(7)

where r is a random individual, $r = \lfloor N \cdot rand(0,1) \rfloor$.

Model 3 Dynamic heuristic crossover model:

$$H_i(SIV) = H_i(SIV) + 0.2(H_i(SIV) - H_r(SIV))(1 - rand(0,1))^{(1-g/g_{\max})^5} \tag{8}$$

where r is a random individual, $r = \lfloor N \cdot rand(0,1) \rfloor$.

The basic structure of perturb migration operator can be informally described in the following algorithm:

Algorithm 1. Habitat perturb migration model

```
for i=1 to N do
    for j=1 to D do
        Use λ_i to probabilistically decide whether to immigrate to x_i,j.
        if rand (0,1)< λ_i then
            Select the emigrating island X_k with a probability μ_k
            Replace the jth decision variable (SIV) of X_i with its corresponding variable in X_j
            x_i,j=x_k,j
        else
            Replace the jth decision variable (SIV) of X_i with its corresponding variable in X_j
            according to different heuristic crossover model
        end if
    end for
end for
```

Hybrid Mutation. In order to enhance the exploration ability of BBO, we use a new mutation operator based on Gaussian operator. The Gaussion mutation can be described as follows:

The formula for the probability density function of the Guassion distribution is

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{9}$$

where μ is the mean and σ^2 is the variance. Then the Guassian mutation with μ= 0 and σ= 1 can be described as

$$x_{i,j} = x_{i,j} + N_j(0,1) \tag{10}$$

Where xi,j is jth dimension variable of individual Xi and Nj(0,1) indicates that the random number is generated a new for each individual of j. In this paper, we use the Guassion distribution to update the individual based sinusoidal migration model.

Algorithm 2 Hybrid with random mutation and Gauss mutation

```
for i=1 to N do
    Compute the probability P_i using λ_i and μ_i
    Use the probability P_i to compute the mutation rate m_i
    for j=1 to D do
        Select a variable (SIV) x_i,j with a probability P_i
        if rand(0,1)<m_i then
            if round(rand(0,1))=0 then
                Replace x_i,j with a randomly generated variable from its range
            else
                Replace x_i,j with Gauss mutation to generate a new SIV
            end if
        end if
    end for
end for.
```

Experimental Results

To evaluate the performance of our algorithm, we apply it to 18 standards benchmark functions. These functions have been widely used in the literature. Since we do not make any modification of these functions, they are given in Table 1.The first five of seven functions are unimodal functions. Function f06 is the step function which has one minimum and is discontinuous. Function f07 is a noisy quadratic function. The following seven functions are multimodal test functions. For these functions, the number of local minima increases exotically with the problem dimensions. Then, ten multimodal test functions with fix dimension which have only a few local search minima are used in our experimental study.

Experimental Seting. For HCBBO, we have chosen a reasonable set of value. For all experiments, we use the following unless a change is mentioned. Population size: NP = 100;Maximum immigration rate: I = 1;Maximum emigration rate: E = 1;Mutation probability: m_{max}= 0.005.All algorithms are coded in MATLAB 2012, and experiments are made on a Pentium 3.0 GHz Processor with 1.0 GB of memory.

Experimental Result. Maximum number of Fitness Evaluation (Max_NFFEs):

The maximum number of generations: 1500 for f1, f6, f10, f12, f13, and f14, 2000 for f2 and f11, 3000 for f7, f8, f9, and 5000 for f3, f4, f5. For all test functions, the algorithms carry out 50 independent runs.

Table 2 Comparisons of Constant HC(sin), Random HC (sin), Dynamic HC (sin).

Function	Max_FFS	Time (s)	sin mode (Constant heuristic crossover)		sin mode (Random heuristic crossover)		sin mode (Dynamic heuristic crossover)	
			Mean	Std dev	Mean	Std dev	Mean	Std dev
*f*01	150000	5.7153	3.3286e-14	2.1303e-13	**1.2534e-52**	2.6303e-52	8.9526e-14	6.1655e-13
*f*02	200000	7.7414	2.2350e-20	1.5803e-19	**1.3785e-46**	1.8124e-46	6.3015e-14	3.9446e-13
*f*03	500000	19.2470	**1.0416e-06**	2.1790e-06	2.9192e-04	2.5396e-04	0.0018	0.0023
*f*04	500000	19.5258	0.0058	0.0037	**9.1256e-06**	6.7277e-06	0.0255	0.0118
*f*05	500000	19.4015	**28.7598**	61.3136	42.0895	27.4098	46.1026	51.4510
*f*06	150000	5.9987	**0**	0	**0**	0	0	0
*f*07	300000	13.1421	4.8462e-04	3.3110e-04	**3.2371e-04**	3.5176e-04	7.1043e-04	5.9618e-04
*f*08	300000	12.2101	-1.25695e+04	7.3498e-12	-1.25695e+04	7.3498e-12	-1.25695e+04	7.3498e-12
*f*09	300000	11.8401	6.6183e-12	3.7993e-11	0	0	0	0
*f*10	150000	11.6959	3.3814e-08	2.3412e-07	**0**	0	0.3526	2.4796
*f*11	200000	7.9892	0.0074	0.0161	**9.8573e-04**	0.0031	0.0019	0.0039
*f*12	150000	6.2042	1.7446e-10	1.2334e-09	**1.6015e-32**	1.2386e-33	0.0021	0.0147
*f*13	150000	6.3539	5.8053e-13	3.9478e-12	**7.9950e-32**	2.4226e-31	1.1408e-14	3.7869e-14
*f*14	150000	6.6176	-78.3323	6.4295e-13	**-78.3323**	0	-78.3323	2.4192e-14

Annotation:Constant heuristic crossover:$H_i\ (SIV) = H_i\ (SIV)+0.12(\ H_i\ (SIV) - H_r(SIV))$
Random heuristic crossover:$H_i\ (SIV)= H_i\ (SIV)+(0.5-rand(0,1))(\ H_i\ (SIV) - H_r(SIV))$

Dynamic heuristic crossover: $H_i(SIV) = H_i(SIV) + 0.2(H_i(SIV) - H_r(SIV))(1-rand(0,1))^{(1-g/g_{\max})^5}$

Conclusion

In this paper, in order to enhance the exploration ability, we proposed a new migration operation used heuristic crossover operator, which is an innovation of the standard BBO migration operator. We have presented three heuristic crossover operators, they are constant heuristic crossover operator, random heuristic crossover operator and dynamic heuristic crossover operator. Among them, the migration operation used random heuristic crossover operator is optimal. At the same time, we have presented a stable mixture mutation approach based on an improved variant of BBO, it is a biogeography of hybrid with random mutation and Gauss mutation based optimization algorithm using sinusoidal migration model. To verify the performance of HCBBO(a migration operation used random heuristic crossover operator), 14 benchmark functions are chosen from literature are employed. The results show that the proposed HCBBO algorithm clearly outperforms the basic BBO.The mixture BBO are stability than other algorithms witch is proposed by now. In this paper, we only consider the global optimization. The algorithm can be extended to solve other problems such as constrained optimization problems.

References

[1] Simon D. Biogeography-based optimization. IEEE Transactions on Evolutionary Computation 2008;12:702–13.

[2] Boussaı¨d I, Chatterjee A, Siarry P, Ahmed-Nacer M. Two-stage update biogeography-based optimization using differential evolution algorithm dbbo. Computers & Operations Research 2011;38(August):1188–98.
[3] Du D, Simon D, Ergezer M. Biogeography-based optimization combined with evolutionary strategy and immigration refusal. In: SMC'09: Proceedings of the 2009 IEEE international conference on Systems, Man and Cybernetics. IEEE Press, Piscataway, NJ, USA; 2009. p. 997–1002.
[4] Ergezer M, Simon D, Du D. Oppositional biogeography-based optimization. In: SMC'09: Proceedings of the 2009 IEEE international conference on systems, man and cybernetics. IEEE Press, Piscataway, NJ, USA; 2009.p. 1009–14.
[5] Gong W, Cai Z, Ling C. DE/BBO: a hybrid differential evolution with biogeography-based optimization for global numerical optimization. Soft Computing—A Fusion of Foundations, Methodologies and Applications; March 2010.
[6] Gong W, Cai Z, Ling C, Li H. A real-coded biogeography-based optimization with mutation. Applied Mathematics and Computation 2010; 216(9): 2749–58.
[7] Li Y, Wu Y, Zhao J, et al. A Kriging-based constrained global optimization algorithm for expensive black-box functions with infeasible initial points[J]. Journal of Global Optimization, 2017:1-24.
[8] Xue Y, Jiang J, Zhao B, et al. A self-adaptive artificial bee colony algorithm based on global best for global optimization[J]. Soft Computing, 2017:1-18.
[9] Popkov A Y, Darkhovsky B S, Popkov Y S. Iterative MC-algorithm to solve the global optimization problems[J]. Automation & Remote Control, 2017, 78(2):261-275.
[10] Zhong F, Li H, Zhong S. An improved artificial bee colony algorithm with modified-neighborhood-based update operator and independent-inheriting-search strategy for global optimization[J]. Engineering Applications of Artificial Intelligence, 2017, 58:134-156.