Particle Swarm Optimization-based Solution Updating Strategy for Biogeography-based Optimization

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Abstract* — Biogeography-based optimization (BBO) is a powerful evolutionary algorithm inspired from the science of biogeography. It mainly uses the biogeography-based migration operator to share the information among individuals. In canonical BBO, according to the principle of immigration and emigration, poor solutions are like to be completely replaced by better ones. Consequently, this will lead to reduction of the population diversity. On the other hand, for Particle Swarm Optimization, a particle will learn from the global best solution and its own history best solution, which also deteriorate population diversity. In this paper, Particle Swarm Optimization (PSO) employs the selection mechanism of BBO and provides its solution updating strategy for BBO. A good particle has a large probability to be learned, while a poor particle has a small probability to be learned. In this way, the whole swarm can eliminate the affects from only one solution. The simulation is done using fourteen benchmark functions, and the results demonstrate that this hybrid BBO-PSO algorithm works efficiently.

Keywords—Biogeography-based Optimization; Population Diversity; Particle Swarm Optimization; Selection Mechanism ; Solution Updating Strategy

I. INTRODUCTION

BBO, as a powerful heuristic algorithm was first proposed by Simon in 2008 [5]. It is established by mimicking the mechanism of species migration among islands, which belongs to the research of science of biogeography. Since then, a number of studies have been done and prove that BBO exhibits excellent optimization performance, not only on various kinds of numerical benchmarks, but also on high-dimensional and multi-objective optimization problems. In original BBO, the algorithm has already outperforms many other evolutionary algorithms for some benchmarks. However, as a novel optimization algorithm, BBO has many aspects can be improved.

In recent years, many studies have been done to improve the performance of BBO. Ergezer and Simon employ opposition-based learning (OBL) alongside BBO's migration rates to create oppositional BBO [7]. Ma and Simon propose blended migration and modify BBO to solve constrained optimization problems in their study [8]. Real-coding method is utilized to represent solutions by Gong[1] to extend discrete optimization to continuous. In addition, Gaussian mutation and Cauchy mutation is adopted to improve the mutation operator of basic BBO. In [21], Guo proposed that standard BBO has a big difference comparing other EAs, which is that BBO's mutation operator is affected by recombination operator, say migration operator. Sinusoidal migration model is proved to be the best migration model by Ma [2] in 2010. Guo discussed classical migration models for BBO in mathematical way [22]. In the study of Zheng [3], DE is used to improve the search performance of BBO and achieved good results. Lohokare[4] uses new mutation function to instead of the old one to improve the convergence performance of BBO. Meanwhile, Differential Evolution (DE) is also utilized to improve the local search ability of part of candidate solutions.

However, in BBO, the design that poor solutions will be fully replaced by good solutions may result in reduce the searching ability of algorithm and lead to premature. In addition, in PSO, the historical information is recorded, which can help algorithm explore searching area. Hence in this paper, we hybridize the two algorithms. On one hand, the historical information can help BBO increase the ability to search. On the other hand, the migration mechanism in BBO will eliminate the affects from only one solution, say the *gbest* in PSO.

The rest of this paper is organized as follows. In Section II, brief of BBO will be introduced. In Section III, the hybrid strategy will be presented. The simulation results will be compared and discussed in Section IV. We end this paper with conclusion in Section V.

II. BIOGEOGRAPHY-BASED OPTIMIZATION

A. INTRODUCTION to SCIENCES of BIOGEOGRAPHY

Biogeography is a discipline which aims to research the natural distribution of species. In nature, species distribute in different habitats which are relatively independent and the species migrate among the habitats some times. The migration process is shown in Fig.1.

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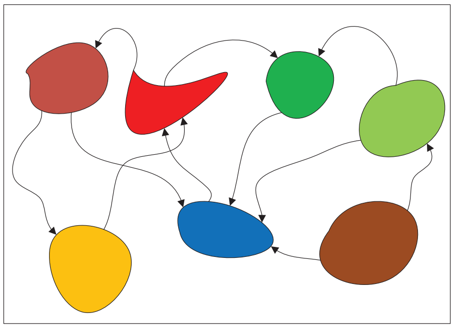

Fig. 1. Migration process

In Biogeography, Habitat Suitability Index (*HSI*) is an indicator to evaluate the quality of a habitat. If a habitat is suitable for species living, it as a high value of *HSI*, while a habitat has a small value of *HSI* if it is not suitable for species living [5].

B. BIOGEOGRAPHY-BASED OPTIMIZATION: BBO

BBO is established using the principle of nature migration in biogeography. Over the course of nature migration, species migrate between habitats according to the changes of habitats' *HSI*. Initially, species leave the habitats with lower *HSI* and be willing to live in the habitats with higher *HSI*. However, as the species number increases, the *HSI* of a habitat decreases since the average resources on this habitat for each species reduce. As a result, species in this habitat would like to leave and to find another better habitat. In addition, due to the mutation, a poor habitat may become suitable for species living. By mimicking the migration and mutation, BBO has two important operators: migration operator and mutation operator respectively. A habitat can be considered as a candidate solution, which is a vector constructed by feasible features called *SIV* (Suitability index variables). In migration operator, individuals exchange their *SIVs* (feasible solutions) to share good information according to the immigration rate and emigration rate which are calculated based on *HSI*. This process is more like species migration. This information exchange process can be shown in (1).

$$Population(i).chrom(k) = Population(j).chrom(k) \quad (1)$$

Then, through the evolution, BBO can find the best habitat (solution). The pseudo-codes are shown in Algorithm I.

Algorithm I: Pseudo-codes of BBO

```
for k=1 to N
       Select a habitat Population(k) with probability proportional to λi
       if rand(0,1)<λi
          for j = 1 to Np
                   Select another Population(SelectIndex)
                   with probability proportional to μi
                   if rand(0,1)<μj
                       Island(k,j)=Population(SelectIndex).chrom(j)
                   Else
                       Island(k,j)=Population(k).chrom(j)
                   End
          End
       End
End
```

where N, λi, Np and μi represent the total number of individuals, immigration rate, number of *SIVs* in one individual and emigration rate respectively. Matrix *Island* is used to update the *population.*

Up to now, many migration models have been proposed, such as linear migration model, sinusoidal migration model, trapezoidal migration model and so on. In this paper, we choose the linear migration model as shown in Fig.2.

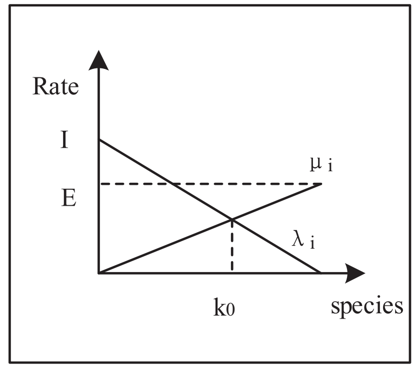

Fig. 2. Linear migration model

In Fig.2, k_0 is the equilibrium number of species, which denotes that the immigration and emigration rates are equal, I is the maximum possible immigration rate and E is the maximum possible emigration rate.

In mutation operator, an *SIV* should be selected randomly, and mutate according to the mutation probability. Clear duplicates operator can eliminate duplicates and reproduce new *individuals*. These three operators form an evolution loop of BBO.

Obviously, there is a problem in migration operator according to (1), which is that one *SIV* is totally replaced by another one, which means the population diversity reduces. Thus, some information in population lost.

III. HYBRID ALGORITHM OF PSO AND BBO

As discussed above, we know that although BBO is an effective algorithm to handle optimization problems, it does no have a suitable strategy to maintain population diversity. In this section, we will provide an overview of the PSO and propose a new method to improve BBO.

A. Particle Swarm Algorithm: PSO

PSO is a kind of population-based evolution algorithm. Each individual of the population is called particle and represent a candidate solution. Every particle has two properties, velocity and position respectively. Meanwhile, for each particle, the historical best positions are recorded. To search the good position, both the personal best position (*pbest*) of a particle and the global best position (*gbest*) of the *population* should be utilized to calculate the new particle position according to the updating formula (2). In (2), r_1 and r_2 are two random real values belonging to interval [0, 1]. Hence, the updating of particles involves both its historical best position and the current global best position of Population.

$$\begin{cases} v_i(t+1) = v_i(t) + r_1 \cdot \Delta_1 + r_2 \cdot \Delta_2 \\ \Delta_1 = \left(p_i(t) - x_i(t)\right) \\ \Delta_2 = \left(p_g(t) - \left(x_i(t)\right)\right) \\ x_i(t+1) = x_i(t) + v_i(t+1) \end{cases} \quad (2)$$

B. A new Hybrid Algorithm: BBO-PSO

As mentioned above, since PSO records the historical information, it can provide BBO more information for evolution, its position updating method can be used to improve the exploring ability of BBO.

$$\begin{cases} Island(k,j) = H_{SelectIndex}(SIV) + r_3 \cdot \Delta_1 + r_4 \cdot \Delta_2 \\ pbest = Chrom\_history\_best(SelectIndex).chrom(j) \\ \Delta_2 = \left(gbest(j) - Population(SelectIndex).chrom(j)\right) \\ gbest = Global\_best\_chrom(j) \\ \Delta_1 = \left(-pbest(j) + Population(SelectIndex).chrom(j)\right) \\ H_{SelectIndex}(SIV) = Population(SelectIndex).chrom(j) \end{cases} \quad (3)$$

Thus, we adopt PSO to improve the exploring ability of BBO. An individual should be updated using its *pbest*, *gbest* of *population* and another *individual* selected. This new update model is shown in (3). In (3), r_3 and r_4 are two random numbers between 0 and 1. $Chrom\_history\_best$ and $Global\_best\_chrom$ are two matrixes which are established to store the *pbest* of each *individual* and the *gbest* of the *population* respectively. The new hybrid migration operator is shown in Algorithm II. Then a simulation is done with using fourteen benchmark functions and the results will be shown in the next section.

Algorithm II: Pseudo-codes for BBOPSO

```
for i=1 to N
  Select a habitat Population(k) with probability proportional to λi
  if rand(0,1)<λi
    for j = 1 to Np
          Select another Population(SelectIndex)
      with probability proportional to μi
      if rand(0,1)<μj
              Island(k,j)=HSelectIndex (SIV)+r3·Δ1+r4·Δ2
          Else
              Island(k,j)=Population(k).chrom(j)
      End
    End
  end
end
```

IV. Simulation and Discussion

In this section, we make a simulation experiment using fourteen benchmark functions. And the results will be shown in this part.

A. Bechmarks

To test the new hybrid algorithm, fourteen benchmark functions are employed as shown in Table I.

TABLE I. BENCHMARK FUNCTIONS

Function	Name	Domain
F1	Ackley	-30≤ x ≤30
F2	Fletcher	-π≤ x ≤π
F3	Griewank	-600≤ x ≤600
F4	Penalty1	-50≤ x ≤50
F5	Penalty2	-50≤ x ≤50
F6	Quartic	-1.28≤ x ≤1.28
F7	Rastrigin	-5.12≤ x ≤5.12
F8	Rosenbrock	-2.0481≤ x ≤2.048
F9	Schwefel	-65.536≤ x ≤65.536
F10	Schwefel2	-100≤ x ≤100
F11	Schwefel3	-10≤ x ≤10
F12	Schwefel4	-512≤ x ≤512
F13	Sphere	-5.12≤ x ≤5.12
F14	Step	-200≤ x ≤200

More details of these benchmarks can be find in [9], [10], and [11]. Seven other popular EAs are also used to compare with the new algorithm BBO-PSO. They are GA[12, 13], PBIL [14], standard PSO [15, 16, 17], ACO [18, 19], and ES [21].

Additionally, for BBO and BBO-PSO, parameters are set as follows: habitat modification probability is set as 1, maximum immigration and emigration rate for each island is 1, and mutation probability is set as 0.05. More details about other EAs can be found in [5]. Each algorithm has a *population* size of 50. The maximum iteration is set as 1000. We run 20 simulations of each algorithm on each benchmark to get representative performance.

B. Results and Discussions

In this simulation, the mean optimization results and the best optimization results of each EAs are shown in Table II and Table III.

TABLE II. MEAN OPTIMIZATION RESULTS

Function	GA	PBIL	PSO	BBO
F1	6.96E+00	1.86E+01	1.44E+01	7.58E-01
F2	2.20E+04	3.44E+05	3.33E+05	**1.72E+04**
F3	1.28E+00	1.71E+02	5.17E+01	1.02E+00
F4	5.40E-02	3.92E+07	1.17E+06	1.55E-02
F5	6.04E-01	1.18E+08	8.14E+06	8.35E-02
F6	1.93E-06	1.09E+01	1.49E+00	2.84E-07
F7	2.63E+01	2.00E+02	1.37E+02	1.01E-01
F8	3.88E+01	1.29E+03	3.43E+02	2.24E+01
F9	4.50E+01	4.28E+03	3.63E+03	**4.44E+00**
F10	2.90E+03	9.82E+03	5.41E+03	3.88E+02
F11	3.89E+00	5.37E+01	2.73E+01	8.00E-02
F12	1.86E+01	5.90E+01	3.52E+01	6.42E+00
F13	9.23E-02	5.31E+01	1.52E+01	1.01E-03
F14	1.30E+01	1.91E+04	5.67E+03	1.80E+00

Function	BBOPSO	ACO	ES
F1	**1.07E+00**	5.89E+00	8.87E+00
F2	9.51E+03	4.30E+05	5.52E+05
F3	**1.00E+00**	1.15E+00	9.80E+01
F4	**1.01E-02**	9.07E+07	3.95E+07
F5	**8.19E-02**	1.78E+08	1.13E+08
F6	**3.62E-07**	3.40E-03	1.47E+01
F7	**1.23E-02**	7.39E+01	2.18E+02
F8	**1.66E+01**	8.41E+02	2.48E+03
F9	1.55E+02	3.16E+01	2.94E+03
F10	**1.83E+02**	1.96E+03	1.29E+04
F11	**1.17E-02**	2.20E+01	7.54E+01
F12	**1.33E+00**	2.02E+01	2.10E+01
F13	**2.34E-04**	8.02E+00	6.77E+01
F14	**2.30E-01**	2.11E+01	1.59E+04

TABLE III. BEST OPTIMIZATION RESULTS

Function	GA	PBIL	PSO	BBO
F1	3.50E+00	1.67E+01	1.09E+01	3.69E-01
F2	1.83E+03	1.84E+05	1.87E+05	3.14E+03
F3	1.06E+00	1.02E+02	2.63E+01	1.01E+00
F4	4.10E-03	4.35E+06	5.25E+04	1.28E-03
F5	1.23E-01	2.40E+07	1.10E+06	2.91E-02
F6	4.50E-07	4.68E+00	3.80E-01	5.00E-08
F7	1.14E+01	1.74E+02	1.09E+02	**0.00E+00**
F8	9.84E+00	4.04E+02	1.72E+02	1.47E+01
F9	3.83E+00	3.14E+03	2.68E+03	**1.47E+00**
F10	1.01E+03	5.59E+03	3.09E+03	1.41E+02
F11	1.40E+00	4.39E+01	1.48E+01	**0.00E+00**
F12	7.00E+00	4.26E+01	2.75E+01	3.70E+00
F13	1.01E-02	2.94E+01	8.64E+00	**0.00E+00**
F14	1.00E+00	1.27E+04	2.70E+03	1.00E+00

Function	BBOPSO	ACO	ES
F1	**1.00E-02**	4.05E+00	6.66E+00
F2	**4.64E+02**	2.62E+05	1.97E+05
F3	**1.00E+00**	1.05E+00	5.97E+01
F4	**1.00E-04**	2.29E+01	2.66E+06
F5	**7.60E-03**	1.35E-32	1.91E+07
F6	**0.00E+00**	1.30E-03	4.87E+00
F7	6.74E+00	5.18E+01	1.70E+02
F8	**1.06E+01**	3.94E+02	1.03E+03
F9	1.46E+02	9.85E+00	2.30E+03
F10	**1.16E+02**	4.62E+02	7.33E+03
F11	8.00E-03	5.70E+00	4.80E+01
F12	**1.17E+00**	6.40E+00	1.29E+01
F13	**0.00E+00**	2.73E+00	3.59E+01
F14	**0.00E+00**	9.00E+00	1.02E+04

For all of these EAs, Table II shows that the mean optimization results of the new hybrid algorithm BBO-PSO are better than other EAs in most cases. Just for Fletcher and Schwefel, the mean optimization results of BBO-PSO are the second best, which is benefit from the healthy population diversity. Besides, the best optimization results, which are shown in Table III, indicate that in the process of the evolution, BBO-PSO performs better in searching the minimum than others in most cases. It shows that BBO-PSO works more efficient than all the other EAs in finding out the minima on the following four benchmarks.

V. CONCLUSIONS

In this paper, we hybridize BBO and PSO to propose a new evolutionary algorithm. It uses the selection mechanism of BBO to select two candidate solutions, and employs the idea in PSO to record historical information. In this way, the population diversity increases. A set of fourteen benchmarks is used to test and compare the proposed algorithm with several popular EAs. The results demonstrate the proposed algorithm is feasible and effective to deal with optimization problems.

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