Application and Performance Comparison of Biogeography-based Optimization Algorithm on Unconstrained Function Optimization Problem

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Abstract—Biogeography-based optimization (BBO) algorithm realizes the information circulation and sharing by the species migration among habitats and achieves the global by improving the adaptability of habitats. Based on the population adaptive migration mechanism of BBO algorithm, the unconstrained function optimization problem is solved with six species migration models. For performance comparison, the ant colony optimization (ACO) algorithm, the differential evolution (DE) algorithm and the particle swarm optimization (PSO) algorithm are adopted to solving six unconstrained functions optimization problems. Simulation results show that the convergence speed, optimization accuracy and solution uniformity of BBO algorithm have been improved significantly, and BBO algorithm is more efficient to solve the unconstrained function optimization problem.

Index Terms—biogeography-based optimization algorithm, function optimization, performance comparison

I. INTRODUCTION

The nature of function optimization problem is to find the optimal solution of an objective function through iterative [1]. The function features are usually described as continuous, discrete, linear, non-linear, convex function, etc. In that the constraint function optimization problem can be converted into unconstrained problem by using the designed special operators and penalty functions to make solution always feasible, the unconstrained function optimization problem is the main research focus. The swarm intelligent optimization algorithms [2] are a kind of random search algorithm to simulate the biological population evolution and evolution, which solves the complex global optimization problems through individual cooperation and competition between species, and is applied in many fields, such as multi-objective optimization, data mining, network routing, signal processing, pattern recognition, etc. The typical swarm intelligence optimization algorithms include Ant Colony Optimization (ACO) algorithm [3], Genetic Algorithm (GA) [4], Bat Algorithm (BA) [5], Artificial Bee Colony (ABC) algorithm [6], etc.

Artificial bee colony (ABC) algorithm is inspired by the foraging behavior of honey bee swarm. Inspired by PSO, an improved artificial bee colony (ABC) algorithm called gbest-guided ABC (GABC) algorithm was proposed by incorporating the information of global best (gbest) solution into the solution search equation to improve the exploitation [7]. In that ABC is good at exploration but poor at exploitation, and its convergence speed is also an issue in some cases, an improved ABC algorithm called I-ABC was proposed, where inertia weight and acceleration coefficients are introduced to modify the search process [8]. A new modified genetic algorithm with adaptive elitist-population strategies was proposed for solving continuous function optimization, which is based on the concept of adaptively adjusting the population size according to the individuals’ dissimilarity and a novel direction dependent elitist genetic operator [9]. A hybrid niching algorithm based on the PSO was proposed to deal with multimodal function optimization problems [10], where the recombination-replacement crowding strategy that works on the archive population is introduced to improve the exploration capability. An ensemble of differential evolution algorithms employing the variable parameter search and two distinct mutation strategies in the ensemble was proposed to solve real-parameter constrained optimization problems, which was tested using benchmark instances [11]. An improved fruit fly optimization (IFFO) algorithm was proposed for solving continuous function optimization problems. A new control parameter is introduced to tune the search scope around its swarm location adaptively and a new solution generating method is developed to enhance accuracy and convergence rate of the algorithm [12]. Cuckoo search algorithm which reproduces the breeding strategy of the best known brood parasitic bird, the cuckoos has demonstrated its superiority in obtaining the global solution for numerical optimization problems. An improved cuckoo search algorithm with adaptive step size adjustment is introduced and its feasibility on a variety of benchmarks is validated [13].

Biogeography-based optimization (BBO) Algorithm is put forward by Simon in 2008 [14-15], whose basic idea is the
species migration to complete the information flows among habitats. By adjusting immigration rate, emigration rate, migration topology, migration interval and migration strategies, the information sharing is realized in the migration process in order to improve the suitability of habitats and obtain the optimal solution [16]. BBO algorithm has been successfully applied in economic load assignment [17], combinatorial optimization [18], power distribution of wireless sensor network [19], function optimization [20], etc. In this paper, based on the population adaptive migration mechanism of BBO algorithm, the unconstrained function optimization problem is solved with six species migration models. The remainder of this paper is organized as follows. In Section 2, the BBO algorithm is introduced. The simulation experiments and the analysis of the results are discussed in detail in Section 3. The concluding remarks are presented in the last section.

II. BIOGEOGRAPHY-BASED OPTIMIZATION ALGORITHM

A. Biogeography

BBO algorithm [14] is derived from biogeography, whose main contents is to establish mathematical models for a series of events include residence, migration routes, production of new species, and extinction of species in nature. Figure 1 introduces this migration relationship among habitants.

Fig. 1. Multi-habitats in biological geography

In addition to the relationship among these islands, each island has its own factors and survival indicators. For those islands suitable for breeding populations, a higher habitat suitable index (HIS) is obtained. The un-isolated index variables affecting HIS are named as independent habitat variable. However, when the HIS is high, the population on the corresponding island is more crowded, many populations will migrate to other neighboring islands to multiply. Meanwhile, there are other populations from other low HIS islands migrating into this island with higher HIS. The immigration rate of the island with lower HIS is higher than islands migrating into this island with higher HSI. The corresponding island is more crowded, many populations will migrate to other neighboring islands to multiply. When the number of species of the island is 0, the immigration rate is the largest value. The equilibrium point of the number of species on this island is $S_0$, where the immigration rate equals to the emigration rate.

Fig. 2. Species migration model of single island

In BBO algorithm, an island has $S$ species, whose probability is $P_s$. $P_s$ changes within the time $[t, t + \Delta t]$ described as follows.

$$P_s(t + \Delta t) = P_s(t)(1 - \mu_s \Delta t - \lambda_s \Delta t) + P_s(1 - \lambda_s \Delta t + \mu_s \Delta t + 1 - 1 \lambda_s - 1 \Delta t + P_s)$$

When the number of species of the island is $S$, the emigration rate is $\mu_s$ and the immigration rate is $\lambda_s$. Suppose Eq. (1) is established, the number of species is $S$ at the time $t + \Delta t$. Aiming at this situation, it must satisfy at least one of the following conditions.

1. At the time $t$, there are $S$ species in this island. At the time $t + \Delta t$, no species emigrate and immigrate.
2. At the time $t$, there are $S + 1$ species in this island. At the time $t + \Delta t$, there is a species to emigrate.
3. At the time $t$, there are $S - 1$ species in this island. At the time $t + \Delta t$, there is a species to immigrate.

If $\Delta t$ is small enough, the probability of emigration/immigration can be neglected for this species. Define $n = S_{\text{max}}$ and $P_s(S = 0, 1, \ldots, n)$. Then equation $P = [P_s, P_{s+1}, \ldots, P_{n}]$ can be represented as a matrix:

$$P = AP$$

where $A$ is given in the Eq. (4).

$$p = \begin{cases} 
-(\mu_s + \lambda_s)P_s + \mu_s P_{s+1}, S = 0 \\
(\mu_s + \lambda_s)P_s + \mu_s P_{s+1} + \mu_s P_{s+1}, 0 \leq S < S_{\text{max}} - 1 \\
-(\mu_s + \lambda_s)P_s + \mu_s P_{s+1}, S = S_{\text{max}} 
\end{cases}$$

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Fig. 3. Simplified species migration model of single island

\[
\lambda_k = I \left( 1 - \frac{k}{n} \right)
\]

(6)

where \( n = S_{\text{max}} \) and \( k \) equals the number of species. Eq. (4) can be further changed as:

\[
A = E - \frac{1}{n} \begin{bmatrix}
1 & 0 & \cdots & 0 \\
-\frac{1}{n} & \ddots & \cdots & \vdots \\
-\frac{2}{n} & \ddots & \ddots & \vdots \\
0 & \cdots & 0 & 1 - \frac{1}{n}
\end{bmatrix} = EA'
\]

(7)

The probability to accommodate the number of species of each island is given by the following formula:

\[
P_k = \frac{1}{1 + \sum_{j=1}^{k} \frac{\lambda_j \lambda_{j+1} \cdots \lambda_{k+1}}{\mu_j \mu_{j+1} \cdots \mu_{k+1}}} 
\]

(8)

If each island (solution) has the same species migratory curve, that is to say \( S_i \) represents a solution with higher HIS and \( S_i \) represents a solution with lower HIS. The emigration rate of \( S_i \) is lower than the corresponding value of \( S_j \), while the immigration rate of \( S_i \) is higher than the corresponding value of \( S_j \). Through the mobility of each solution, it can make the information sharing among islands. Six species migration models of BBO algorithm are shown in Figure 4.
habitats is obtained. The immigration rate is judged to see whether the habitat is specified or not. If the immigration rate is realized the successive operation, the habitat of the corresponding habitat, the number of all species are denoted as \( S_i \) and immigration rate \( \mu_i \). By comparing the habitat values of \( S_i \) with \( S_{\text{max}} \), the number of all species are denoted as \( n \). Then the rest habitat population \( S_i \) is realized the successive reduction \( i \) according to \( H_i \) from good to bad, that is to say \( S_i = S_{\text{max}} - i \) \( (i = 1, 2, \ldots, n) \). By the above calculation, the emigration rate \( \mu \) and immigration rate \( \lambda \) of \( H_i \) in the different migration model can be obtained. Also the species contained probability \( P(K_i) \) of \( H_i \) can be calculated.

\[
M_S = M_{\text{max}}(1 - \frac{P}{P_{\text{max}}}) \tag{9}
\]

So the mutation rate \( M_i \) of each \( H_i \) is obtained. The global variable is composed of the maximum emigration rate \( E \), the immigration rate \( I \), the mutation rate \( M_{\text{max}} \), the individual reservations elitist number \( Z \) and the global mobility rate \( P_{\text{mod}} \) of species.

The flowchart of BBO algorithm is shown in Figure 5. The algorithm procedure is described as follows.

Step 1: Initialize the parameters of BBO algorithm and the \( H_i \) vector of any habitat.

Step 2: For different suitability \( H_i \), sort the habitats from good to bad. Generally the update rate of habitats \( i = 1 \).

Step 3: By comparison, judge whether the desired optimum is satisfied or not. If it is satisfied, the optimum is output and algorithm procedure is terminated. Otherwise, turn to Step 4.

Step 4: Suppose the maximum number of a specie in a habitat \( S_{\text{max}} = n \). Then by means of \( S_i = S_{\text{max}} - i \) \( (i = 1, 2, \ldots, n) \), the populations value \( S_i \) of habitat \( i \) is obtained, which is further brought into the migration model to obtain its \( \lambda_i \) and \( \mu_i \).

Step 5: After the cyclic operation of \( P_{\text{mod}} \), whether \( i \) has entered into the immigration pattern (the number \( n \) of \( i \) is defined as the number of cycles) can be determined. If habitat \( i \) is satisfied or not. If it is satisfied, the optimum is output and algorithm procedure is terminated. Otherwise, turn to Step 4.

Step 6: By calculating \( M_i \) of the corresponding habitat, the related variable of the Habitat \( i \) is judged to see whether the mutation has occurred. The results are compared and turn to Step 2.

![Fig. 4. Six species migration models of BBO algorithm](image-url)

C. BBO algorithm

The BBO algorithm is a method composed by \( n \) habitats with \( D \) -dimension \( SIV \) fitness vector. \( H_i \) represents the fitness value of the habitat \( i \). By comparing the habitat values of \( H_i \) with \( S_{\text{max}} \), the number of all species are denoted as \( n \). Then the rest habitat population \( S_i \) is realized the successive reduction \( i \) according to \( H_i \) from good to bad, that is to say \( S_i = S_{\text{max}} - i \) \( (i = 1, 2, \ldots, n) \). By the above calculation, the emigration rate \( \mu \) and immigration rate \( \lambda \) of \( H_i \) in the different migration model can be obtained. Also the species contained probability \( P(K_i) \) of \( H_i \) can be calculated. The emigration rate \( \mu \) is determined by selecting, and then the feature component \( SIV_{ij} \) of the \( i \) is replaced by a component of selected \( m \).

III. SIMULATION EXPERIMENTS

In this paper, ant colony optimization (ACO) algorithm, differential evolution (DE) algorithm and particle swarm optimization (PSO) algorithm are chosen for realizing the
performance comparison with six Benchmark functions (Ackley function, Griewank function, Rastrigin function, Sphere function, Step function, and Quartic function). Their input parameters are defined as $x_i (i = 1, 2, \ldots, n)$. The global minimum point is $x^* = (0, \ldots, 0)$ and the minimum of the objective function is $f(x^*) = 0$. These six testing functions are described as follows.

In this paper, the parameters of each optimization algorithm are roughly adjusted in order to obtain better performance, but the parameters of any algorithm are not fine-tuned specially. The adopted parameters are described as follows. In ACO algorithm, the pheromone evaporation coefficient is 0.9 and the quality factor of the pheromone is 1. In DE algorithm, the weight factor and the cross-constant are 0.5. In PSO algorithm, the inertia constant is 0.3, the cognitive constant is 1 and the particle swarm interaction constant is 1. In BBO algorithm, the habitat update probability is 1, the mobility range of each generation is $[0, 1]$, the step length of probability integral calculation, the maximum immigration and the emigration rate are all 1. For each algorithm, the population size is 50 and the maximum iteration number is 50.

The simulation results are shown in Figure 6-11. The statistics results are shown in Table 1 and Table 2.

(1) Ackley function:  
$$f_1(x) = 20 + e - 20e^{-\left(0.5 \sum_{i=1}^{n} x_i^2 \right)} - e^{\sum_{i=1}^{n} \cos(2\pi x_i)}, -32 \leq x_i \leq 32, \min(f_1) = 0.$$  

(2) Griewank function:  
$$f_2(x) = \frac{1}{4000} \left(\sum_{i=1}^{n} x_i^2\right) - \left(\prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right)\right) + 1, -600 \leq x_i \leq 600, \min(f_2) = 0.$$  

(3) Rastrigin function:  
$$f_3(x) = \sum_{i=1}^{n} \left(x_i^2 - 10 \cos(2\pi x_i) + 10\right), -15 \leq x_i \leq 15, \min(f_3) = 0.$$  

(4) Sphere function:  
$$f_4(x) = \sum_{i=1}^{n} x_i^2, -100 \leq x_i \leq 100, \min(f_4) = 0.$$  

(5) Step function:  
$$f_5(x) = \sum_{i=1}^{n} \left|x_i + 0.5\right|^2, -100 \leq x_i \leq 100, \min(f_5) = 0.$$  

(6) Quartic function:  
$$f_6(x) = \sum_{i=1}^{n} x_i^4 + \text{random}(0, 1), -1.28 \leq x_i \leq 1.28, \min(f_6) = 0.$$
It can be seen from Figure 6-11, the BBO algorithm is behaved very well compared with other three swarm intelligent algorithms in five benchmark functions in addition to seem slightly less in Ackley function. The iteration number of BBO algorithm is about 20 times to be leveled to the minimum, which proves that the algorithm is more rapid and efficient in global function optimization problem. Seen form the simulation results, the optimal solution and the average value of the BBO algorithm for five benchmark functions are both at the forefront position. For Ackley function, it is slightly inferior to ACO and DE algorithm. The simulation results may indicate that BBO algorithm is the most effective in terms of solving function optimization problems, the DE and ACO algorithm secondly, the PSO algorithm has worst performance.

IV. CONCLUSION

In that the current optimization algorithms have poor convergence in solving function optimization problems, the BBO algorithm is used to solve the function optimization problem. The simulation experiments are carried out with multiple test functions to verify it’s optimization performance. Simulation results show that BBO algorithm can solve function optimization problems more efficiently. The convergence speed and optimization accuracy are higher than other intelligent optimization algorithms. These results also indicate deep-seated that the biogeography mechanism is the law of nature in the formation of long-term evolution and it is unique and effective in handling all kinds of optimization problems.

REFERENCES


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