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Research paper

A Novel Approach for Testing Benchmark Functions using Biogeography based Optimization (BBO) Algorithm

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Abstract

Biogeography is the science and study of geographical distribution of biological organisms. BBO is a traditional algorithm that maximises efficiency, based on the mathematical aspects of biogeography. The project aims at sharing the probable features between solutions and fitness values that are represented as immigration and emigration between islands. BBO is similar to biological optimization methods i.e. Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) that carries features which are unique. The proposed algorithm of BBO provides a solution to many that uses GA and PSO. This paper demonstrates a performance of the proposed BBO with a set of well known standard benchmark functions.

Keywords: *Biogeography, evolutionary algorithms, optimization, BBO*.

1. Introduction

The biogeography was first traced by Alfred Wallace [1] and Charles Darwin [2] in the nineteenth century. Robert MacArthur and Edward Wilson [3] worked on mathematical models of biogeography, focussing on the species distribution among islands that are near.

The concept of Biogeography formulates how new species arise, and the way they migrate from one island to another. This also describes to know the means of a species becoming extinct. These kinds of analysis and formulation in terms of biological species distribution models, implies taking care of the islands quality and its habitat zones. Considering the existence of species and its living, an area that acquires and possess the resources to make a species sustain in all terms are said to have a high island suitability index(ISI)[5]. Certain characteristics that correlate with the ISI are termed as suitability index variables (SIV). They include factors like rainfall, temperature, a diverse vegetation, its topography , temperature and the area of land that are made available. Taking into account with these SIV and ISI parameters, SIV is considered as independent variables and ISI as dependent variables of the island. The reobtained inferences attract large number of species and large populations with a high ISI value and the other parts with a low crowd. A good solution to an optimization problem is like an island with high ISI and high species diversity and vice versa.

Highly fit solutions oppose change more than low diversity solutions. The highly fit and the low fitness solutions are shared. This results in having the features in both the high and low fitness solutions. This kind of feature is similar to a species that keeps moving to a new habitat while remaining species stay stable in their own land. Poor solutions accept many features from good solutions. This addition of features tends to raise their quality to poor solutions.

2. Biogeography

Figure 1 gives feature z can be emigrated from x and immigrated to y. The immigration rate λ and emigration rate μ are the functions of total species in the habitat.

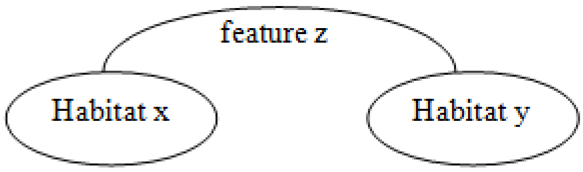

Fig. 1: Immigration and Emigration

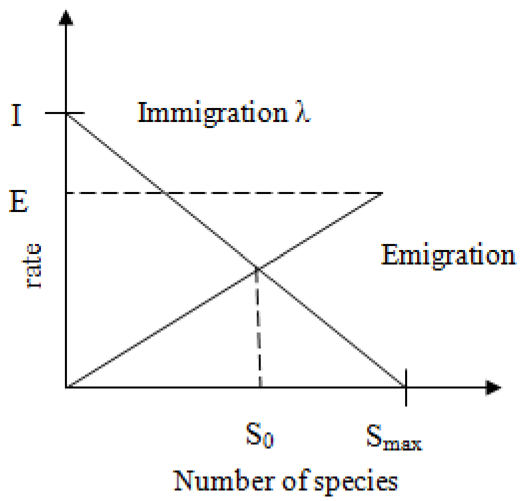

Fig. 2: A model of species abundance in a single habitat [3]

Figure 2 illustrates the result of a species for an island adapted from [3]. The equilibrium number of species is S_0 at which, the point of immigration and emigration rates are equal. Consider the immigration curve and maximum immigration rate denoted as I. It can occur only when zero species in the habitat. The results imply if the number of species grows, and then the habitat becomes more occupied leading to a heavy crowd. The other species can survive in the habitat successfully thereby decreasing the immigration rate. The maximum numbers of species that can be supported in S_{max} at immigration rate become zero. Consider the emigration curve and maximum emigration rate denoted as E. If no species are found in the habitat then the E becomes zero. The increase in the number of species makes the habitat crowded and unsafe place to live. If more species start evacuating from their habitat, E increases. At the point where both I and E are equal, the equilibrium number of species can be denoted as S_0. From the straight line curves shown in the figure2, we have,

$$\mu_k = \frac{Ek}{n}$$

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

Now consider we have E=I, then

$$\lambda_k + \mu_k = E$$

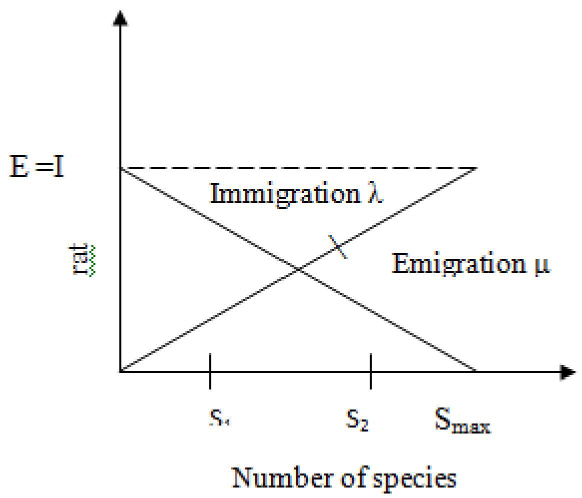

Fig. 3: Illustration of two candidate solutions to some problem

Figure 3 illustrates the solutions proposed using symmetric immigration and emigration curves which results in poor and good solutions indicated by S1 and S2 respectively.

3. Biogeography based Optimization (BBO)

In the proposed BBO, the solutions obtained are represented by islands that are analogous to species. From this comparison, we arrive at a conclusion that the island with GA's which represent the population are entirely yield different results. The following are the fundamental differences between BBO and traditional evolutionary algorithms

• Reproduction does not form a part in BBO, even though it is a population-based optimization algorithm

• The unique feature of BBO is that each solution uses its own fitness to decide whether or not to receive other solution's feature.

3.1. Migration

In the candidate solution, the population is represented as vectors of integers and each integer in the solution vector denoted as SIV. Good solutions for the proposed system implies habitats that has high ISI and poor ISI values are extremely solutions for poor ones. ISI is analogous to "fitness". High ISI solutions can represent many species in habitats. Low ISI solutions can represent less species in habitat. Assuming that E = I, the value S can be represented by the solutions which depends on ISI. Figure 3 represents S_1 with low ISI solution and S_2 with high ISI. S_1 has low species and S_2 has many species. By doing so, $\boldsymbol{\lambda_1}$ **for** $\mathbf{S_1} > \boldsymbol{\lambda_2}$ **for** $\mathbf{S_2}$ and μ_1 for $S_1 < \mu_2$ for S_2. These solutions derived for the emigration and immigration rates of each solution are required to know the existence of a species or information about a species residing at a particular habitat. This can be modified based on the result obtained from the other. The solution that is been selected for modification can use λ to decide whether to modify each SIV. If a given solution S_i is selected to be modified in a given SIV, μ can be used to decide whether the solution migrate from SIV to S_i at random.

3.2. Mutations

The concept of mutation that influences to change the ISI of a natural habitat results in a different value than that of its equilibrium values such as neighbouring habitat, disease, natural catastrophes. It can also change due to random events. The mutation rates can be determined using SIV mutation and the species count probabilities. The following differential equation can be used to find the probabilities of each species count.

$$P_s = \begin{cases} -(\lambda_s + \mu)P_s + \mu_{+1}P_{s+1}, S = 0 \\ -(\lambda_s + \mu)P_s + \lambda_{s-1}P_{s-1} + \mu_{+1}P_{s+1}, 1 \le S \le S_{max} \\ -(\lambda_s + \mu)P_s + \lambda_{s-1}P_{s-1}, S = S_{max} \end{cases}$$

Figure 3 depicts the fact that when compared to medium species count, low and high species counts contain low probabilities. If a given solution S has a low probability P_s, then it can be likely to mutate to some other solutions.

$$m(S) = m_{\max}\left(\frac{1 - P_s}{P_{\max}}\right)$$

Where m is mutation rate and m_{max} is user-defined parameter. Based on this method, there is a chance to improve the low ISI solutions to mutate.

4. BBO Algorithm

This section gives the algorithm for biogeography based optimization

(1) Initialize a set of solutions to a problem.
(2) Compute "fitness" for each solution.
(3) Compute S, λ, μ for each solution.
(4) Modify habitats based on λ, μ.
(5) Mutation based on probability.
(6) Typically we can implement elitism.
(7) Go to step 2 for next iteration if needed.

5. Simulation Results

The results obtained from the simulation of BBO algorithm are provided. The performance evaluation of BBO algorithm is conducted using well known benchmark function given in the Table 1.

5.1. Parameter Setting

The experiments are carried out on MATLAB. The process sis repeated for 30 times with random seeds, for all the benchmark function that is already mentioned in the Table 1.

5.2. Experimental results

Table 1 shows the experimental results of Ackley, Step, Sphere, Griewank, Rastrigin, Rosenbrock functions of BBO algorithm. The convergence curves of BBO show the progress of the best values. In graph, generations can be plotted on x-axis and the fitness value on y-axis. Figure 4-9 shows the convergence curve of Ackley, Step, Sphere, Griewank, Rastrigin, Rosenbrock functions of BBO algorithm. The convergence graphs are presented in the following section for those conclusions arrived from the results.

5.3. Discussions

The performance of BBO for both unimodal functions like step, sphere and multimodal functions like Griewank and Ackley works effectively. The Ackley function finds the optimum value to an extent by providing many local optima. The proposed BBO produces an efficient result for non – separable Ackley when compared to the separable Rastrigin. The performance of Sphere and Step provides a optimal solution in most of the trials. In Griewank , the converging results lead to an interesting pattern while the proposed algorithm can converge to global optimal level for complex multimodal functions .The results of uninodal function are more optimized , therein with a lesser degree difference as compared to the other complex functions. Thus the proposed BBO algorithm is much more efficient for both unimodal and multimodal benchmark functions.

Table 1: Benchmark Functions

Function	Formula	Dimension	Range
Ackley	$\left[f(x) = -20\exp\left(-0.2*\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos 2\Pi x_i\right) + 20 + e \right]$	20	±30
Griewank	$f(x) = (1/4000)*\sum_{i=1}^{D}(x_i)^2 - \prod_{i=1}^{D}\cos(x_i/\sqrt{i}) + 1$	20	±600
Rastrigin	$f(x) = \sum_{i=1}^{n}\left(x_i^2 - 10\cos(2\Pi x_i) + 10\right)$	20	±5.12
Rosenbrock	$f(x) = \sum_{i=1}^{n}\left(100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2\right)$	20	±2.048
Sphere	$f(x) = \sum_{i=1}^{n}\left(x_i^2\right)$	20	±5.12
Step	$f(x) = \sum_{i=1}^{n}(x_i + 0.5)^2$	20	±200

Table 2: Results obtained from BBO algorithm for Benchmark functions

Function	Best Optimized values for BBO algorithm
Ackley	0.5103
Griewank	1.0027
Rastrigin	1.0109
Rosenbrock	0.0077
Sphere	0.0101
Step	0.0006

Table 3: Comparison between BBO with other evolutionary algorithms

Function	ACO	BBO	DE	GA
Ackley	0.0379	0.5103	0.5131	0.6018
Griewank	1.0436	1.0027	1.0019	1.0119
Rastrigin	0.0770	1.0109	1.0462	1.0109
Rosenbrock	0.0474	0.0077	0.0045	0.0088
Sphere	0.5039	0.0101	0.0003	0.0101
Step	0.0002	0.0006	0.0001	0.0001

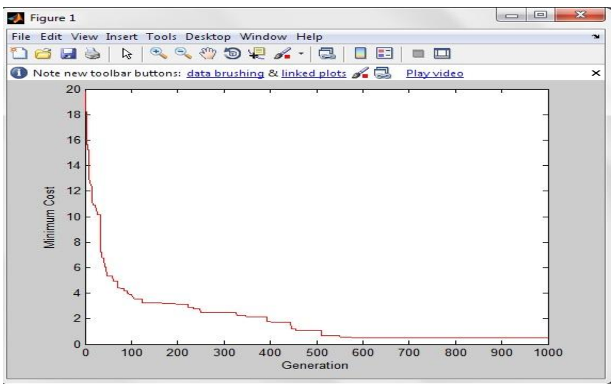

Fig. 4: Ackley function

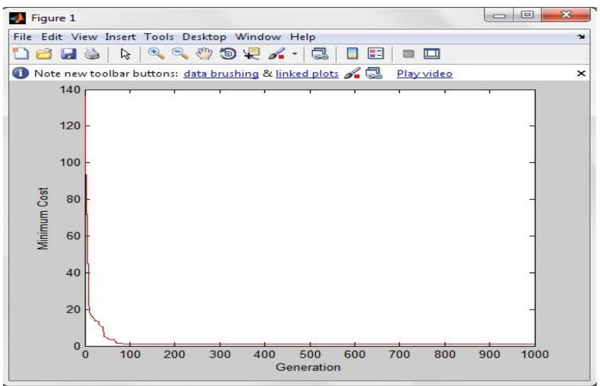

Fig. 5: Griewank function

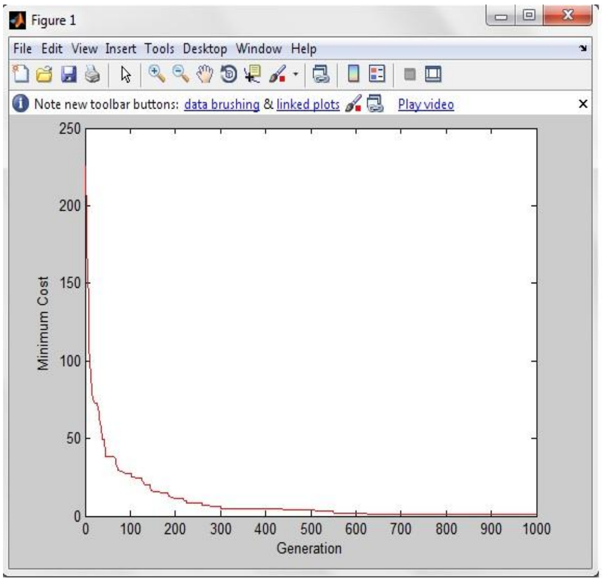

Fig. 6: Rastrigin function

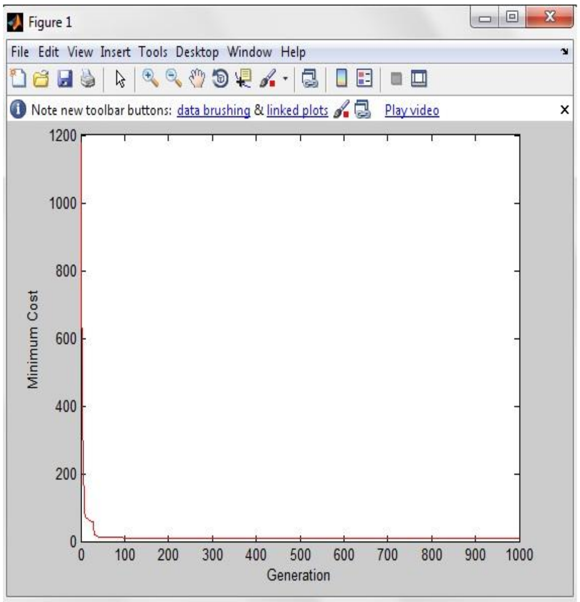

Fig. 7: Rosenbrock function

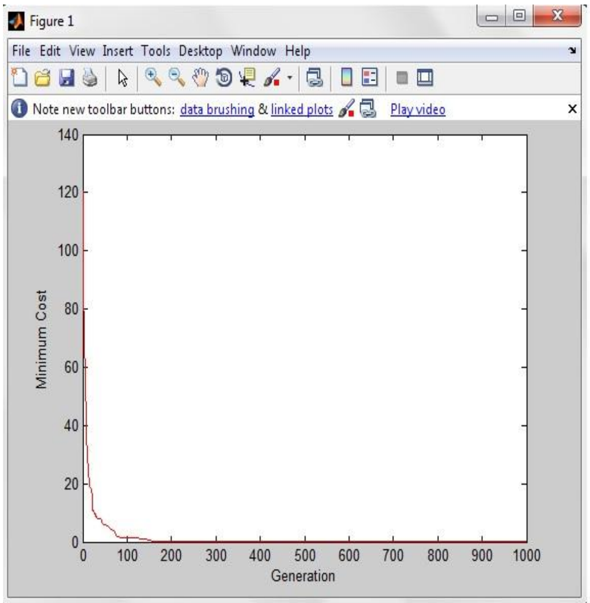

Fig. 8: Sphere function

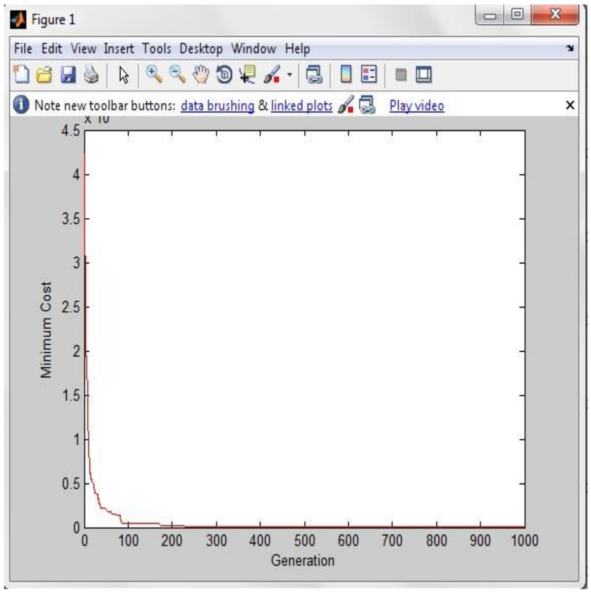

Fig. 9: Step function

6. Conclusion

From this proposed solution, we tend to provide a novel approach for solving BBO and has been implemented with various experimental trials and also tested using the various benchmark functions that are available. By the use of this algorithm, we try to provide an optimized result considering the functions. From the list of available functions, it is found that Griewank function produces a good result with BBO and gets optimum value, although being a complex function. Thus these results infer us that the other functions both simple and complex, executes a fast convergence thereby resulting in greater accuracy. By the use of all these algorithms, it is better planned to make use of BBO for engineering applications

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