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Beetle Antennae Search Algorithm Based on PSO and Fibonacci

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Abstract. Beetle Antennae Search Algorithm (BAS) is simple and efficient, but is not stable. The calculation precision is not high and the algorithm is easy to get into local optimum. To overcome these defects, the idea of particle swarm is used to search and traditional Fibnacci method to determine the search step length of each set up, so as to propose the PSO-Fibonacci-BAS algorithm. In this paper, single - peak and multi - peak function are used to test the performance of PSO-Fibonacci-BAS and three evaluation criteria are established to evaluate the performance of the algorithm. The simulation results show that PSO-Fibonacci-BAS is better than PSO and BAS. The algorithm not only has strong stability, but also has high precision.

Keywords: Beetle antennae search algorithm, Fibonacci algorithm, PSO.

1. Introduction

Intelligent search algorithm [1] is a kind of search technology which is inspired by biological evolution mechanism or social behavior mechanism. Because of simplicity and efficiency, it attracted a lot of attention in the past ten years, and played an important role in both computer and engineering fields. Scientists proposed a number of intelligent algorithms, including genetic algorithms[2], simulated annealing[3], taboo search[4], neural networks[5] and so on. The algorithm is based on the most nutrient-rich place in the water, which is the most nutritious place. This feature is used to simulate the foraging behavior of fish. In 1995, Kennedy and Eberhart were inspired by the research results of the behavior of birds, and proposed the particle swarm optimization algorithm[6]. In the particle swarm optimization algorithm, a group of particles are randomly initialized in the feasible solution space. Studies show that the above as a novel evolutionary algorithm of swarm intelligence algorithm, can effectively solve the problem of most optimized, and its potential parallelism and distributed characteristics for processing a lot of in the form of database data provided technical guarantee. However, compared with other mature optimization algorithms, the research of swarm intelligence algorithm is still in its initial stage, and there are still many problems to be studied in depth, which can be summarized as follows: (1) The comparative study between swarm intelligence algorithm and other more mature optimization algorithms is insufficient, and the fusion research of other intelligent methods and advanced technologies is not sufficient. (2) "There is no free lunch" theorem shows that there is no optimization algorithm is applicable to any problems, therefore, further study of the scope of application of swarm intelligence algorithm and further expand the application field of each algorithm is a very necessary.

Recently, Jiang et al. proposed Beetle Antennae Search Algorithm which does not need the specific form of the function, no gradient information is required, and the optimization can be achieved. However, the algorithm is prone to local optimum, low precision and unstable. In order to solve the shortcoming of the Algorithm, Beetle antennae Search Algorithm based on particle swarm and Fibonacci Algorithm is proposed in this paper. The test results show that the PSO-Fibnacci-BAS algorithm not only has high accuracy, but also has high stability.

2. Background-Beetle Antennae Search Algorithm

Beetles Antennae Search was inspired by the beetle's foraging principle. When the crustaceans forage, they do not know where the food is, but forage according to the strength of the smell. A beetle has two long horns. If the antenna on the left is stronger than the one on the right, then the next beetle will fly to the left, otherwise it will fly to the right. According to this simple principle, beetles can find food efficiently. The smell of the food in the beetle's search is like a function. This function value is different at each point in three dimensions. The beetle's two whiskers should be able to pick up the odor value of two nearby points, and the beetle's goal is to find the spot with the largest global odor value.

For the sake of illustration, we denote the position of the beetle as a vector x t at t-th time instant (t=1,2,...) and denote the concentration of odor at position x to be $f(x)$ known as a fitness function, where a maximum value of $f(x)$ corresponds to the source point of the odor.

The search for a function is the same as that of the beetle foraging. Firstly, to model the searching behavior, we propose describing a random direction of beetle searching as follows,

$$\overrightarrow{dir} = \frac{rand(n,1)}{norm(rand(n,1))} \tag{1}$$

where $\overrightarrow{dir}$ denotes direction, and n represents the dimensions of position. Furthermore, we present the searching behaviors of both right-hand and left-hand sides respectively to imitate the activities of the beetle s antennae:

$$x_r = x_t + d_t \overrightarrow{dir}\,, \quad x_l = x_t - d_t \overrightarrow{dir} \tag{2}$$

where x_t represents the location of the search area at time t, d_t represents the search step at time t , represents the position of the left search area, and x_r represents the position of the right search area.

Secondly, to formulate the behavior of detecting, we further generate iterative model as follows to associate with the odor detection by considering the searching behavior,

$$x_t = x_{t-1} + \delta_t \overrightarrow{dir} \times sign(f(x_r) - f(x_l)) \tag{3}$$

where δ represents the search step after fixed direction. The initialization of δ should be equivalent to the searching area. $Sign$(•) represents a sign function.In terms of searching parameters, i.e., antennae length d and step size δ, examples of update rules are presented for the designer as follows,

$$d_t = c_1 d_{t-1} + c_2\,, \delta_t = c_1 \delta_{t-1} \tag{4}$$

where c_1 and c_2 represent fixed constants. Beetle Antennae Search Algorithm steps as follow:

Table 1 Beetle Antennae Search Algorithm steps

Algorithm 1: BAS algorithm for global minimum searching
Input: Establish objective function $f(x_t)$, where variable $x_t = [x_1, \cdots, x_i]^T$ initialize parameters x_0, d_0, δ_0 .
Output: x_{best}, f_{best}
While ($t < T_{\max}$) or (stop criterion) **do**
Generate the direction vector unit $\overrightarrow{dir}$ according to (1); Search in variable space with two kinds of antennae according to (2); Update the state variable t according to (3)
if $f(x_t) < f_{best}$ **then**
$f_{best} = f(x_t)$, $x_{best} = x_t$
Update sensing diameter d and step size δ with decreasing functions (4) respectively, which could be further studied by the designers.
Return x_{best}, f_{best}

3. Beetle Antennae Search Algorithm based on PSO and Fibonacci

Both the direction and the initial point of the search algorithm are given randomly, and only one beetle is used for searching. The test results also show that the stability and accuracy are extremely low. In order to solve this problem, this paper takes two measures. Firstly, we sent a number of cattle to search, thus increasing the probability of finding the optimal value by random searching. Secondly, the traditional Fibnacci method is used to optimize the step length, so that the optimal value can be found in each direction. Beetle Antennae Search Algorithm based on PSO and Fibonacci, the algorithm is calculated as follows:

Firstly, this time it was not a beetle, but P beetles. Randomly generate P initial points and compute the function values.

$$x_{0i} = rands(n,1)(i = 1,2,\cdots,P) \;,\; f_i = f(x_{0i}) \tag{5}$$

where x_{0i} is the initial point, and f_i is the value of the function. Ten beetles will set out at the same time to search for food. Every time the beetles searched in a random direction, the search direction was as follows:

$$\overrightarrow{dir_i} = \frac{rand(n,1)}{norm(rand(n,1))} \tag{6}$$

where $\overrightarrow{dir_i}$ denotes direction, and n represents the dimensions of position. Furthermore, each beetle's search behavior is shown below, and it should be noted that each beetle's step length is obtained by using Fibnacci method:

$$x_{ri} = x_{ti} + d_{ti}\overrightarrow{dir_i} \;,\; x_{li} = x_{ti} - d_{ti}\overrightarrow{dir_i} \tag{7}$$

where x_{li} represents the position of the left search area.

According to the above principle, the iterative model expression is as follows:

$$x_{ti} = x_{ti-1} + \delta_{ti}\overrightarrow{dir_i} \times sign\left(f\left(x_{ri}\right) - f\left(x_{li}\right)\right) \tag{8}$$

$$\delta_{ti} = rand \tag{9}$$

Table 2 PSO-Fibonacci-BAS Algorithm steps

Algorithm 2: PSO-Fibonacci-BAS algorithm for global minimum searching
Input: Establish objective function $f(x_{ti})$, where variable $x_{ti} = [x_1,\cdots,x_i]^T$ initialize parameters x_0, d_0, δ_0.
Output: x_{besti}, f_{besti}
While ($t < T_{\max}$) or (stop criterion) **do**
Generate the direction vector unit $\overrightarrow{dir_i}$ according to (6); Search in variable space with two kinds of antennae according to (7); Update the state variable t according to (8)
if $f\left(x_{ti}\right) < f_{besti}$ **then**
$f_{besti} = f\left(x_{ti}\right)$, $x_{besti} = x_{ti}$
(9) is taken into the target function $f\left(x\right)$, and the Fibnacci method is used to obtain the optimal d_{ti} of the target function in this direction.Update sensing step size δ_{ti} with function (9) respectively, which could be further studied by the designers.
Return x_{besti}, f_{besti}

4. Algorithm simulation and analysis

In order to prove that PSO-Fibnacci-BAS has higher computational accuracy and stability, 8 standard test functions are selected for testing. Meanwhile, PSO-Fibnacci-BAS algorithm is compared with the PSO algorithm and the original tenor.

4.1 Test Functions

The test functions selected in this paper cover single - peak function and complex multi-peak function. These functions include, Rosenbrock, Sphere Model, Schaffer’ s f6, An extension of the axis parallel hyper-ellipsoid, Moved Axis parallel hyper-ellipsoid, Sum of different power, Shubert. The specific form of each test function is shown in Table 3.

Table 3 Test function

funcname	Test function	Search space	Theoretical optimum	The number of iterations
Rosenbrock	$f(x)=\sum_{i=1}^{N-1}\left[100*\left(x_i^2-x_{i+1}\right)^2+\left(1-x_i\right)^2\right]$	[-5.12,5.12]	0	100
Sphere Model	$f(x,y)=x^2+y^2$	[-5.12,5.12]	0	100
Schaffer’s f6	$f(x,y)=0.5+\frac{\sin^2\sqrt{x^2+y^2}-0.5}{\left(1+0.01\times\left(x^2+y^2\right)^2\right)^2}$	[-10,10]	0	100
An extension of the axis parallel hyper-ellipsoid	$f(x,y)=\sum_{i=1}^{N}\left(\sum_{j=1}^{i}x_j\right)^2$	[-100,100]	0	100
Moved Axis parallel hyper-ellipsoid	$f(x,y)=5\times x^2+10\times y^2$	[-5.12,5.12]	0	100
Sum of different power	$f(x)=\sum_{i=1}^{N}\lvert x_i\rvert^{i+1}$	[-1,1]	0	100

4.2 Experimental Evaluation Criteria

In this paper, PSO-Fibnacci-BAS algorithm, PSO algorithm, and Beetles Antennae Search algorithm are compared. The number of iterations of each algorithm is 100, among which the PSO-Fibnacci -BAS algorithm and PSO algorithm have 30 initial particles. In order to evaluate the algorithm objectively, this paper will give several evaluation criteria:1) The global optimum value is selected in the 40 run results;2) Calculate the average of the 40 run results;3) Calculate the standard deviation of 40 running results.

4.3 Experimental Results and Analysis

The experimental results under two-dimensional conditions are shown in Table 4 and Fig. 1. According to the above three evaluation criteria, PSO, BAS, PSO-Fibonacci-BAS, three algorithms are evaluated.

Table 4 The experimental results under two-dimensional conditions

funcname	algorithm	Global optimum	Mean Best	Standard deviation
Rosenbrock	PSO	1.6900e-06	3.5688e-05	4.2444e-05
	BAS	0.0965	1.3929	2.9464
	PSO-Fibonacci-BAS	0	0	0
Sphere Model	PSO	1.0400e-07	8.0980e-07	8.2490e-07
	BAS	8.1400e-42	3.0422e-40	3.3853e-40
	PSO-Fibonacci-BAS	0	0	0
Schaffer’s f6	PSO	2.2500e-08	1.8612e-06	3.3775e-06
	BAS	0.0096	0.0874	0.1384
	PSO-Fibonacci-BAS	0	0	0
An extension of the axis parallel hyper-ellipsoid	PSO	1.3000e-07	1.2437e-06	1.4676e-06
	BAS	1.5000e-05	2.9192e-04	2.8098e-04
	PSO-Fibonacci-BAS	0	0	0
Moved Axis parallel hyper-ellipsoid	PSO	4.46E-08	9.40E-06	1.35E-05
	BAS	0.000214	0.0011599	0.001599223
	PSO-Fibonacci-BAS	0	0	0
Sum of different power	PSO	1.30E-08	2.10E-07	2.92E-07
	BAS	1.50E-06	0.00011377	0.00014333
	PSO-Fibonacci-BAS	0	0	0

From the evaluation criterion 1 (global optimal solution), whether the single-peak function or multi-peak function, PSO is more accurate than BAS, but it can not reach the optimal value of theory. The PSO-Fibonacci-BAS algorithm proposed in this paper can achieve the optimal theoretical value; From the evaluation standard 2 (mean best), the test results of the six single peak function show that only the average of the PSO-Fibonacci -BAS algorithm in the three algorithms is the optimal value of the theory. The test results of the Shubert function and the Hansen function also show that the average value of the PSO-Fibonacci -BAS algorithm is the closest to the theoretical optimal value; From the evaluation standard 3 (standard deviation), the test results show that the stability of PSO-Fibonacci -BAS is the best in the three algorithms. The stability of the test results is particularly strong in the unimodal function, and the fluctuation is very small in the multimodal function. According to the above three evaluation criteria, the stability and calculation accuracy of PSO-Fibonacci-BAS are higher than that of PSO and BAS.

5. Summary

The original beetle search algorithm is easy to get into local optimum, poor stability and low precision. In this paper, the PSO-Fibonacci -BAS algorithm is proposed, and multiple beetles are sent to search, and the traditional Fibnacci method is used to determine the step length of each step. According to the experimental results, 6 of the 8 test functions can reach the optimal value of the theory, and the other two are very close to the optimal value of the theory. The PSO-Fibonacci-BAS algorithm is better than PSO and BAS algorithm. PSO-Fibonacci-BAS algorithm has strong stability, high computational accuracy and fast convergence speed, which is a good algorithm for optimizing performance.

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