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Applying Fusion of Pso-Abc Algorithm on the Minimax Location Problem

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Abstract: In this paper, we propose a fusion of PSO-ABC algorithm based on the research of particle swarm optimization (PSO) algorithm and artificial bee colony (ABC). The former is apt to trap in local optimum, while the later has great ability of global searching and lower convergence speed in the later evolution process. Using the evolution of artificial swam, we gained a global optimum which was applied to the evolution of particle swarm to overcome the basic PSO's shortcomings of slow updating speed in later evolution process and that improved the local search ability of PSO algorithm within feasible region. This novel algorithm can solve the minimax location problem effectively and has a good application value.

Keywords: ABC, fusion algorithm, location problem, PSO.

1. INTRODUCTION

Minimax problem is a sort of non-differentiable optimization problem in mathematics. It can be used effectively to deal with many problems in real life, such as with least amount of work or doing most things in given time. Location problem is such a problem that can use minimax method to determine the optimization location site which will make the farthest site as much nearly as possible. For example, how to select the location site when establishing logistics distribution center, how to locating the place where the event took place to implement emergency rescue for emergency rescue facility when sudden event happens, all the above problems are in the domain of minimax problems, which can be solved with location algorithm[1]. A new algorithm is advanced to solve location problem based on careful study of minimax algorithm, that is, improved fusion of PSO and ABC.

2. PSO AND ABC

2.1. PSO

Suppose that in a D-dimensional target search space, there are n particles which are the solutions of every optimum problem. Each particle has a fitness value determined by optimal function and a speed to determine their flying direction and distance [2]. Then particles will follow the current optimal particle to find their optimal solution in solution space iteratively. In each process of iteration, particles update themselves by tailing after two extremes. One is the optimal solution which is found by the particle itself, called pBest, the other, called gBest, is the optimal solution of the whole swarm. In t-th iteration, the current position of particle i is expressed as follows: xi(t)=(xi1(t),xi2(t),…,xid(t)),its speed is expressed as vi(t)=(vi1(t),vi2(t), …,vid(t));In the process of iteration, the most optimal position searched by the individual particle can be expressed as pi(t)=(pi1(t), pi2(t), …pid(t)),which is called pBest, while the optimal position searched by all particles in the swarm can be presented as pg(t)=(pg1(t),pg2(t), …,pgd(t)),named gBest. In each iteration, particles updating these two extremes according to formula (1) and (2) to adjust their flying speed and direction [3]. After n generation of iterations, the most optimal resolution is obtained.

$$\begin{aligned} vid(t+1) &= w*vid(t)+ \\ & c1*r1*(pid(t)-xid(t)) \\ & +c2*r2*(pgd(t)-xid(t) \end{aligned} \qquad (1)$$

$$xid(t+1) = xid(t) + vid(t+1) \qquad (2)$$

In above formulas, i=1,2, …,n;d=1,2, …,D; r1 and r2 are symmetrical distribution random numbers between 0 and 1; c1 and c2 are learning factors representing acceleration constants of the particles flying to the pBest and gBest, usually c1= c2=2; w is the inertia weight; vid(t)is the speed of particle i at t moment, vid(t+1) is the updating speed after iteration. xid(t) is the position of the particle i at t moment, xid(t+1) is the updating position after iteration. pid(t) is the optimal opposition of particle i at t-moment, it is the recognition part of the particle; pgd(t) is the optimal opposition and is the social part of the particle. The first part of the formula (1) shows the global and local search ability of the particle during excise, by introducing inertia weight.

2.2. ABC Algorithm

Artificial Bee Colony (ABC) algorithm is a kind of metaheuristic intelligence algorithm and was introduced by Karaboga in 2005 [4]. It was inspired by bees foraging behavior to solve the numerical optimization problem. This method was mainly based on the swarm foraging behavior model proposed by Tereshko and Loengarov in 2005, which

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contains three core elements-- employed bees, unemployed bees and food sources. The first two are responsible for searching rich food sources around hive. This model also defines two kinds of guiding mode, that is to say, a positive signal will be fed back to the swarm by rich food sources which would lead more bees to gather honey. Meanwhile, negative signals will also be fed back result in giving up the food sources [5]. Both behaviors are self-organization and swarm intelligence.

In ABC algorithm, the solution of problems to be solved is regarded as artificial food. If the food is richer, the quality of the solution is better [6]. Then a flock of artificial bees will search the rich food for a better solution of the relative problem. The coming problem should first be translated into the most optimal solution by using ABC to find a set of parameter vectors which will make the objective function to be minimum. Artificial bee colony will initialize some solution at random and a better solution is closed by using neighbor search through iteration, thus worse solution is abandoned which improves the quality of solution. In this process, each bee represents a possible solution of the optimal problem. The quality of the nectar source corresponds to the quality of solution which is expressed by fitness [7, 8]. Observing bees will select one of the nectar according to the message shared by honey gathering bees followed by probability formula (3).

$$Pi = F(\theta i)\sum sp = 1F(\theta p) \tag{3}$$

In which, θi is on behalf of the i-th nectar, i∈{1,2,…,S},S represents the number of nectars, F(θi) shows the fitness of the i-th nectar. After comparing to other nectar around θi, observing bees will select one of the nectars. Location of the new nectar is calculated as follows:

$$\theta_i(c+1) = \theta_i(c) \pm \varphi_i(c) \tag{4}$$

In above formula, φi(c) is the renewal step-size near θi generated randomly. If the fitness of a new nectar is better than the original one, that is, F(θi(c+1))> F(θi(c)), observing bee will select a new nectar θi(c+1); Otherwise, it stays unchanged. When the number of loops reaches to the limited count, if the quality of nectar gets little improvement, the honey gathering bees will give up this nectar and turn into observing bees and the location of xi will update as follows:

$$Xi(j) = xmin(j) + \varphi'(xmax(j) - xmin(j)) \tag{5}$$

Here φ' is a symmetrical distributed random number in [0, 1].

3. IMPLEMENTATION OF FUSION ALGORITHM

3.1. Algorithm Principle

In our algorithm, PSO and ABC algorithms are fused together to form a new PSO-ABC algorithm. At first, the particle swarm is divided into PNum sub-swarms with equal size which will evolve on the basis of PSO. Then the best particles of every sub-swarm constitute a new swarm and pick out the best particle after evolution. Because the position of the best particle of each sub-swarm is changed after evolution, the diversity of population is increased [9]. Meanwhile, PSO algorithm can search precisely to find better solution. That the global best particle's position feedbacks into the speed updating formula can lead the PSO to jump out of local optimum effectively[10]. The speed and Location updating formula of PSO-ABC is described here:

$$\begin{aligned} &vid\ (t+1) = w * vid(t) + c1 * r1 * pid(t) \\ &- xid(t)) + c2 * r2 * \mu 1 * (pigd(t) - xid(t)) \\ &+ c3 * r3 * \mu 2 * (Xgd(t) - xid(t)) \end{aligned} \tag{6}$$

$$xid(t+1) = xid(t) + vid(t+1) \tag{7}$$

In above formulas, pigd(t) is the global optimal solution of the set of i-th particle swarm at t-moment and Xgd(t) is the best particle calculated by ABC algorithm.

Compared with standard particle swarms speed formula, formula (6) expands the third and fourth part with two impact factors-μ1 and μ2 (μ1=0.5, μ2=0.25), which makes the fourth part becoming the global optimal feedback. Particle swarm's speed is controlled at a right level, which decreases the impact on optimal particles, maintains the population's diversity and avoids trapping in local optimization [11].

3.2. Algorithm Flow

① Initiate the particle swarm and set relative parameters; ② Divide particles into PNum groups, each has Num particles; ③ Evaluate the fitness of each particle, record optimal particle pigd of each group.; ④ Update the particle swarm according to the formula (6) and (7); ⑤ Update the global optimal point of each group pigd; ⑥ Take the global optimal point of each group pigd as the initial particle of ABC algorithm; ⑦ Update particles according to the ABC updating formula to find the optimal point Xgd; ⑧ If termination condition is satisfied, Xgd is output and algorithm stops; otherwise returns to ④ step.

4. SIMULATING EXPERIMENT AND RESULTS ANALYSIS

To validate the algorithm of this article, the comparison experiment has been processed with the references [1] and [2], implemented in Matlab under the environment of Pentium2.7GHz CPU and 2GB memory. In this experiment, the problems is transformed into inequality constrained optimization problem, the penalty function is used as benefit function to do iteration. The numerical experiment is done under the condition of gradient linear independence assumption without active constraint and the problem of minimal location is solved.

Assume minimal location problem is as follows: For the n points Pi(x,y)(i=1,2,…,n) in a given plane and the surface area of any shape R=UjRj, every Rj is continuous region. Note ∂R as the boundary of R. Depending on the distance measure, Euclidean distance and absolute distance are the two kinds of problems to determine location P(x,y) and result in :min max{[x-xi]2+(y-yi)2]1/2|P∈R∪∂R}.

Example 1 Given 16 points on plane as follows, the results of three kinds of algorithms is shown in Table **1**.

P1=(-9,8),P2=(-15,-8),P3=(22,5),P4=(17,20),P5=(10,0), P6=(3,4),P7=(-5,-9),P8=(-16,-4),P9=(12,4),p10=(-10,7),P11=

Table 1. The results of three kinds of algorithms on example 1.

Algorithm Name	Objective Function Value		Location Point	
	Euclidean Distance	Absolute Distance	Euclidean Distance	Absolute Distance
Reference [1]	52.000	57.210	(-30.000,5.120)	(-30.150,9.940))
Reference [2]	52.000	57.110	(-30.000,5.100)	(-30.000,10.000)
This article	52.000	57.000	(-30.000,5.000)	(-30.000,9.930)

Table 2. The results of three kinds of algorithms on example 2.

Algorithm Name	Objective Function Value		Location Point	
	Euclidean Distance	Absolute Distance	Euclidean Distance	Absolute Distance
Reference [1]	10.640	14.000	(-1.390,1.060)	(-2.300,-0.400))
Reference [2]	10.601	14.000	(-1.300,1.080)	(-1.600,0.500)
This article	10.588	14.000	(-1.311,1.054)	(-1.764,0.365)

(1,14),P12=(-7,6),P13=(-14,,3),P14=(12,24),P15=(-1,1), P16=(0,13)

The composition of region R is as follows:

x-y≤30

-2x-3y≤90

X≤-x+4y

-x+4y≤150

7x+5y≤270

11x-5y≤270

Example 2: Given 12 points on plane as follows, the results of three kinds of algorithms is shown in Table **2**.

The composition of region R is as follows:

4(x-5y-30)≤y2

2x+3y≤60

-x+5y≤100

-9x+y≤240

-x-4y≤150

19x-24y≤60

Seen from Tables **1** and **2**, the results of PSO-ABC have good global search ability and fast convergence speed, which are superior to those of references of [1] and [2] and have the advantages of both PSO and ABC showing a good test effect. When the test results of standard PSO and ABC are not ideal, fusion algorithm can effectively solve the problem. Fusion algorithm can effectively avoid premature convergence and it can approximate gradually to global optimal solution as the search process continues.

CONCLUSION

Swarm optimization problem, particle swarm and artificial swarm fusion algorithm is proposed as PSO - ABC algorithm, and simulation experiments using the minimax location problem's examples show that the results of algorithm proposed in this thesis are better than those of reference [1] and reference [2] algorithm and has good application value.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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