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Optimization Technique of Pheromone-Based Bees Algorithm

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***Abstract*— Bees algorithm (BA) is an optimization algorithm based on a particular intelligent behavior of honeybee swarms. In this study, we propose a new BA containing one of the behavior of honeybee in the natural world. The behavior has the action of a pheromone. This pheromone has the effect to attract other bees. Because many bees are attracted to the best site. Proposed BA can leave from local minima more easily than previous methods. We confirm the performances of proposed BA using the function approximation called a benchmark problem. The pheromone is more effective than standard BA.**

I. Introduction

Bees Algorithm (BA) [1] is generally known as a popular optimization algorithm for the solution of object function and is an evolutionary algorithm to simulate the intelligent honey foraging behavior of honeybee [2]. A honeybee is a social insect which performs group behavior. It is very rare to make this in the world of insect. In the natural world, honey foraging behavior of the bee consists of two types, recruitment behavior and navigation behavior. Recruitment strategies are used to communicate previous search experiences to other members in the beehive. Navigation strategies are used to navigate in unknown world. And, the honey foraging bee consists of two types. There are search-bee and recruit-bee. Search-bee has a role which searches sources of honey and tells it to recruit-bee. Recruit-bee is recruited to sources of honey by search-bee. Next, we explain honey foraging behavior of honeybee. First, search-bee searches sources of honey at random. In order to recruit recruit-bee in the beehive for the source of honey, search-bee tells recruit-bee in the beehive the distance and direction of the source by waggle dance. This dance has a role which gives the source of honey information (e.g. the direction and the distance).

BA consists of a recruitment strategy and a navigate strategy like behavior of honeybee. BA performs a kind of neighborhood searching combined with random search and can be used for both combinatorial optimization problems and functional optimization problems. The strong point of BA is that leaving from local minima is easy. However, BA has a weakness which is difficult to converge.

In nature world, there is a theory that honeybee use pheromone in order to look for sources of honey. Honeybee have one of the most complex pheromonal communication systems found in nature [3]. For example, drones emit a pheromone that attracts other flying drones to promote drone aggregations at sites suitable for mating with virgin queens. However, the existing BAs do not use pheromone action for navigation of recruitment.

In this study, we propose pheromone-based BA (PBBA). The important feature of PBBA is that all bees are influenced by pheromone. A pheromone is emitted by the best evaluation bee among all the bees. When other bees fall into local minima, they can leave from the local minima by being attracted to the pheromone. Therefore, PBBA can easy to leave from local minima and convergence at high speed. In Section II, we explain the algorithm of PBBA in detail. In Section III, we perform basic numerical experiments by using three algorithm methods including PBBA, and confirm the performance of PBBA for functional optimization problems.

II. Pheromone-Based Bees Algorithm

The existing BA algorithm does not use pheromones. The proposed PBBA use pheromones. Pheromone acts to attract bees. Therefore, if pheromone is disposed at the best evaluation site, pheromone attracts all other bees to the best evaluation site.

The algorithm requires several parameters to be set; the number of search-bee M, the number of sites selected out of N visited sites, and the number of best sites out of selected sites b.

Step. 1 PBBA lets a generation step $t = 0$ and the converge step $t_{Ri} = 0$. PBBA disposes the search-bee $i = (1, 2, ..., M)$ position $\boldsymbol{X}_i = (x_{i1}, x_{i2}, ..., x_{iD})$ randomly. D is dimension parameters.

Step. 2 Comparison of the current search-bee fitness value $\boldsymbol{X}_i(t)$. Ranking z_i is made into a high order of evaluation. Best site and good sites are chosen according to a rank.

Step. 3 PBBA disposes the recruit-bee $j = (1, 2, ..., N_i)$ around $\boldsymbol{X}_i$. The value of N is changed by the result of [Step. 2]. PBBA assigns more recruit-bee j to search near to the best site. The recruit-bee position r_{i_j} is decided by following equations

$$r_{i_j d} = x_i(t) + \Delta\phi_{i_j}(t), \tag{1}$$

$$\Delta\phi_{i_j} = (S_i(t)Q_{i_j}, \theta_{i_j}), \tag{2}$$

where θ_{i_j} is the polar coordinate. Q is the random variable distributed uniformly on [0, 1]. θ_{i_j} is the amplitude and is the random variable distributed uniformly on [0, 2π]. S_{i_j} is the largest search range.

Step. 4 PBBA evaluates the all current recruit-bee cost $f(\boldsymbol{R}_{i_j})$. PBBA updates the search-bee position $\boldsymbol{X}_i$ for each i.

Step. 5 If $\boldsymbol{X}_i(t+1) \leq \boldsymbol{X}_i(t)$; PBBA performs [Step. 6]. If $\boldsymbol{X}_i(t+1) > \boldsymbol{X}_i(t)$; PBBA updates each $\boldsymbol{X}_i$, lets $t_{Ri} = 0$ and performs [Step. 7].

Step. 6 If $t_{R_i} < T_R$; PBBA lets $t_{R_i} = 0$ and initializes $S_i(t)$. If $t_{R_i} > T_R$; $S_i(t+1) = 0.9S_i(t)$.

Step. 7 The current cost $\boldsymbol{X}_i$ is evaluated. The global best position x_{gbest} among all X_i is updated. $\boldsymbol{X}_i(t+1)$ is updated according to $\boldsymbol{X}_{Gbest}$. The important feature of PBBA is that the all bees $\boldsymbol{X}$ are influenced by the pheromone. The pheromone is disposed the best position $\boldsymbol{X}_{Gbest}$ in the whole group. Furthermore, pheromone strength differs with distance. The site nearer, $\boldsymbol{X}_{Gbest}$ attracts more strongly. The $\boldsymbol{X}_i$ is updated depending on the best position $\boldsymbol{X}_{Gbest}$.

$$d_i = p \times \frac{M - (z_i - 1)}{M - 1}, \quad (3)$$

$$\boldsymbol{X}_i(t+1) = \boldsymbol{X}_i(t) + d_i Q(\boldsymbol{X}_{gbest} - \boldsymbol{X}_i), \quad (4)$$

where the parameter p is positive acceleration coefficient.

Step. 8 PBBA let $t = t + 1$ and $t_{Ri} = t_{Ri} + 1$. PBBA goes back to [Step. 3], and repeats until $t = T$.

III. SIMULATION RESULTS

A. Benchmark Functions

In order to evaluate the performance of PBBA, we apply PBBA to some benchmark problems. The problems have the optimum (minimum) values of $f(x)$ in the algorithm. We use the following four benchmarks.

1. Rosenblock function :

$$f_1(x) = \sum_{d=1}^{D}(100(x_d^2 - x_{d;1})^2 + (1 - x_d)^2), \quad (5)$$

where $x \in [-2.048, 2.048]^D$ and the optimum solution x^* are all $[1, 1, ..., 1]$.

2. Sphere function :

$$f_2(x) = \sum_{d=1}^{D} x_d^2, \quad (6)$$

where $x \in [-5.12, 5.12]^D$ and the optimum solution x^* are all $[0, 0, ..., 0]$.

3. Stretch function :

$$f_3(x) = \sum_{d=1}^{D}((x_d^2 + 1 + x_d^2)^{0.25}(1 + \sin(50(x_d^2 + 1 + x_d^2)^{0.1})^2, \quad (7)$$

where $x \in [-10, 10]^D$ and the optimum solution x^* are all $[0, 0, ..., 0]$.

4. Rastrigin function :

$$f_4(x) = 10D + \sum_{d=1}^{D}\big(x_d^2 - 10\cos(2\pi x_d)\big), \quad (8)$$

where $x \in [-5.12, 5.12]^D$ and the optimum solution x^* are all $[0, 0, ..., 0]$.

The functions f_1 and f_2 are unimodal function, f_3 and f_4 are multimodal functions which have numerous local minima. Therefore, in the case of multimodal functions, the solution lapsed into local minima easily. All the functions have the dimension parameter D. In this study, D is set 100 to investigate the performance for different dimensions. We carry out the simulation 10 times with 2000 generations.

B. Simulation Results

In order to evaluate the performance of PBBA and investigate behavior of PBBA, we compare the three algorithms; BA, PBBA, and particle swarm optimization (PSO) [4]. BA is the general BA method which does not use pheromone. PBBA is the proposed algorithm explained in Section II. PSO is popular optimization method for the solution of object function, and has the character similar to the pheromone of PBBA. Therefore, we used PSO for the comparison. The parameters of BA and PBBA are set as follows;

$$M = 20, b = 2, e = 6, N_1 = 9, N_2 = 5, z_i = 0.02$$

where b is the number of the best sites, e is the number of the elite sites, N_1 is the number of recruit-bee in best sites, and N_2 is the number of recruit-bee in elite sites.

The parameters of the PSO was set as follows;

$$c_1 = c_2 = 1.8, w = 0.5, K = 60$$

where c_1 and c_2 are the acceleration coefficients, w is the inertia weight, and K is the number of particles. K is the same as the total number of bees in BA and PBBA.

The result for the 100 dimensional functions are summarized in Table I.

TABLE I
COMPARISON OF BA, PSO AND PBBA RESULTS WITH $D = 100$.

f		BA	PSO	PBBA
f_1	Avg.	136.97	177.36	**97.40**
	Min.	96.20	92.43	95.73
f_2	Avg.	9.03e-016	0.23	**3.47e-022**
	Min.	9.43e-017	1.81e-006	3.71e-023
f_3	Avg.	259.34	195.04	**150.81**
	Min.	245.91	165.58	123.87
f_4	Avg.	770.07	439.41	**200.98**
	Min.	702.54	358.25	163.17

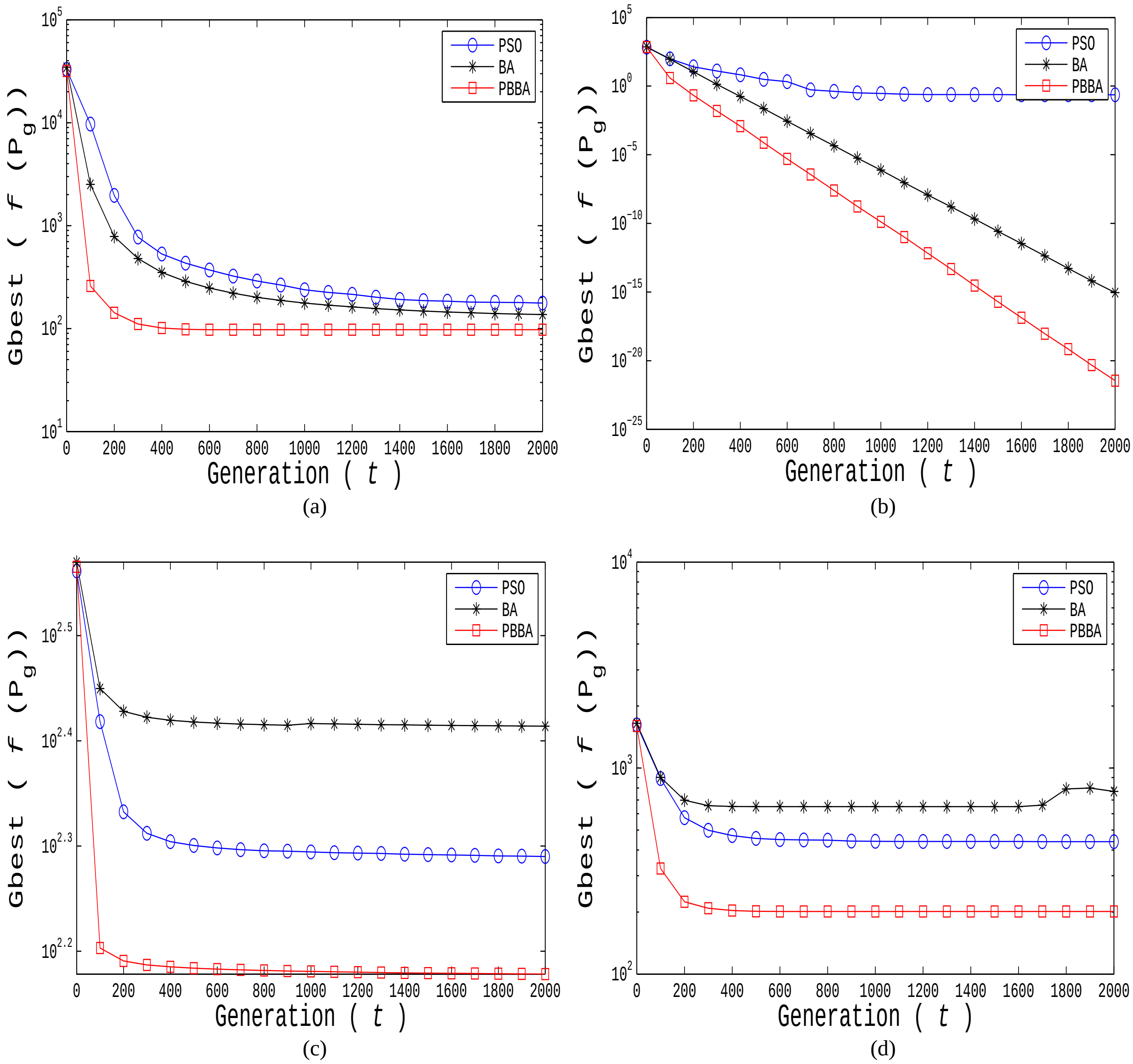

Fig. 1. Average *gbest* value of every generation for 100-dimensional four functions. (a) Rosenblock function. (b) Sphere function. (c) Stretch function. (d) Rastrigin function.

The performances of PBBA are the best evaluation among the three algorithms. Because it is difficult for PSO to find the optimum solution for high-dimensional functions. PSO lapse into the local minima and prematurely converges. From Fig. 1, this is because that the pheromone action of PBBA worked effectively to multimodal functions. From these results, we can refer that PBBA is the effective algorithm, and that it is worth to add the action of pheromone to BA.

IV. Conclusions

In this study, we have proposed pheromone-based bees algorithm (PBBA) and have confirmed that the PBBA could obtain the effective results especially for two functional optimization problems in used function approximation. A pheromone has an effect which attracts a bee. Therefore, PBBA was able to converge at high speed on the optimal solution without lapsing into local minima. Because of this, this pheromone was effective. In future works, we want to add different effects to the pheromone action.

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