Effectiveness of Guidepost Pheromone for Honeybee Colony Optimization

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***Abstract*—Honeybee Colony Optimization (HCO) is an optimization algorithm based on a particular intelligent behavior of honeybee swarms. In this study, we propose a new HCO containing a characteristic of guidepost pheromone that has the effect to attract other bees. Namely, many bees can move to the optimal place. We investigate the performance of the proposed HCO by using four benchmark problems. It discovered that the effect of guidepost pheromone works well for the high dimension problems. We consider that the proposed HCO with pheromone can leave from local minima more easily than the standard HCO.**

I. Introduction

Honeybee colony optimization(HCO) [1] is known as one of the optimization techniques used for optimization problems such as a linear programming, and this is an evolutionary algorithm to simulate the intelligent foraging behavior of honeybee swarms [2] [3].

First, we explain food foraging behavior of honeybee in the real world (see. Fig. 1). There are two types of honeybee, i.e., search-bee and recruit-bee. Search-bee searches the mellow food source by exploring the circumference at random. When search-bee finds the mellow food source, search-bee returns to the hive and does the waggle dance [4] to send a suitable number of recruit-bees to the food source. This waggle dance is combined recruitment behavior and navigation behavior. Recruitment behavior means that search-bee tells the result of searching for food to the other bees which are waiting in the hive. And a suitable number of recruit-bee is sent to the mellow food source. Navigation behavior means that search-bee teaches the information of the food place to other honeybees which are waiting in the hive, and search-bee guides recruit-bee to the food place. Search-bee can inform the other bees of the information of food place such as distance, direction and evaluation of the food place by doing the waggle dance. Namely, the suitable number of recruit-bees go to the food source correctly. The honeybees can behave as a group by containing these two kinds of honeybees. This action is rare in the insect, then the honeybee is called social insect.

The standard HCO is modeled on the above food foraging behavior of honeybee. It is confirmed that HCO is effective on combinatorial optimization problems and functional optimization problems by using neighborhood searching combined with random searching. The important characteristics of HCO are as follows. It is obtained high efficiency by combing the several simple roles. It is easy to escape from local minima. However, there is a problem. The convergence speed of HCO is slow by searching the solution space widely.

Next, we consider the pheromone of honeybee [5]. Although the ant and the termite are well known as insect using a pheromone, it has turned out that the honeybee also uses the pheromone by research. There are several kinds of pheromones and each pheromone has different characteristics to the others. We focus on a guidepost pheromone. When a certain honeybee finds the food source, the guidepost pheromone is left to the return road as landmark, in order to deliver the information of food source to the other honeybees which are waiting in the hive.

In this study, we propose Pheromone-Based Honeybee Colony Optimization (PBHCO). PBHCO contains the guidepost pheromone which has property to attract the other honeybee. The important feature of PBHCO is that all honeybees are influenced by pheromone. We assume that PBHCO can escape from local minima by effect of the pheromone. By computer simulations, we confirm that PBHCO can converge with high speed than the standard HCO by avoiding the local minimum problem.

II. Pheromone-Based Honeybee Colony Optimization

In this study, we propose the new HCO with the guidepost pheromone. This optimization system is named Pheromone-Based Honeybee Colony Optimization (PBHCO). PBHCO contains the characteristics of the guidepost pheromone which has action to attract other bees. The pheromone is disposed at the best evaluation site by search-bee and the pheromone attracts all other bees to the best evaluation site. The pheromone is disposed by search-bee at the best site $\boldsymbol{X}_{Gbest}$ in the whole space and the other bees are attracted this site $\boldsymbol{X}_{Gbest}$ at every updating steps. When the obtained solution is better than the previous one, the pheromone is disposed to new solution site and the other bees are attracted to new solution site from the next generation. The algorithm requires several parameters to be set; the number of search-bee M, the number of sites

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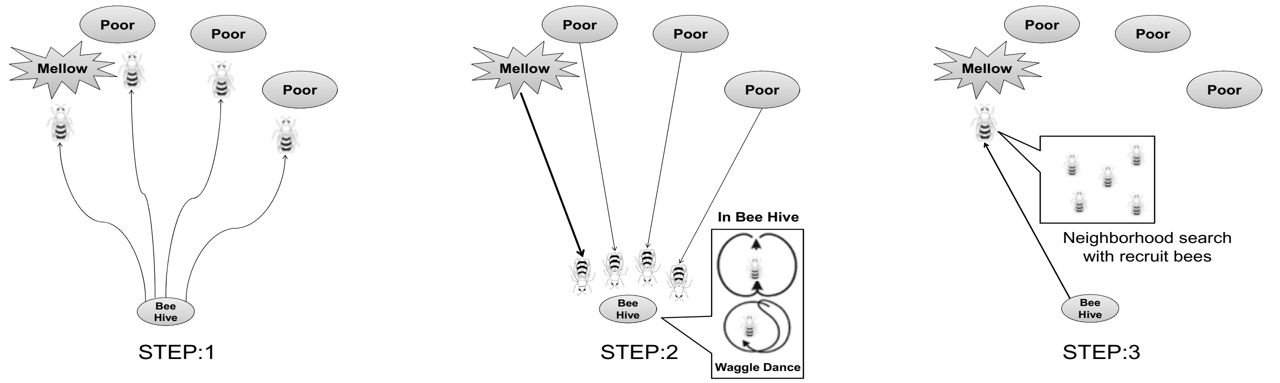

Fig. 1. Food foraging behavior of honeybee

selected out of N visited sites, and the number of best sites out of selected sites b.

We explain the process of PBHCO algorithm in detail as follows. The flowchart of PBHCO is also shown in Fig. 2.

Step. 1 PBHCO lets a generation step $t = 0$ and the converge step $t_{Ri} = 0$. PBHCO disposes the search-bee $i = (1, 2, ..., M)$ at random.

Step. 2 Position information $\boldsymbol{X}_i(t) = (x_{i1}, x_{i2}, ..., x_{iD})$ in search-bee is evaluated. And it is ranked z_i as the high order of evaluation and the best position and a comparatively good position are determined as order from a top. Comparison of the current search-bee fitness value $f(\boldsymbol{X}_i(t))$. D is dimension parameters.

Step. 3 Dispose the recruit-bee $j = (1, 2, ..., N_i)$ around $\boldsymbol{X}_i$. Recruit-bee is disposed around each $\boldsymbol{X}_i$ in the high order of evaluation according to the rank performed by [Step. 2]. The formula which determines the position information r_{i_j} on recruit-bee is shown below.

$$r_{i_j} = x_i(t) + rand[0, 1] \cdot S_i(t) \tag{1}$$

where S_i is the largest search range of recruit bee.

Step. 4 Evaluate the cost $f(\boldsymbol{R}_{i_j})$ in all recruit-bee in current generation$t$. Update the search-bee position $\boldsymbol{X}_i$ for each i.

Step. 5 If $f(\boldsymbol{R}_{i_j}) \leq f(\boldsymbol{X}_i(t))$; Lets $t_{Ri} = t_{Ri} + 1$, PBHCO performs [Step. 6].
If $f(\boldsymbol{R}_{i_j}) > f(\boldsymbol{X}_i(t))$; PBHCO updates the position information on each $\boldsymbol{X}_i$, lets $t_{Ri} = 0$ and performs [Step. 7].

Step. 6 If $t_{R_i} < T_R$; PBHCO lets $t_{R_i} = 0$ and initializes $S_i(t)$.
If $t_{R_i} > T_R$; $S_i(t + 1) = \alpha \cdot S_i(t)$.
where α is parameter to which convergence is urged.

Step. 7 Evaluate the current cost $\boldsymbol{X}_i$ in all bees. 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 PBHCO 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 ranking. The rank higher, $\boldsymbol{X}_{Gbest}$ attracts more strongly. The formula of the strength of the pheromone in ranking is shown in the following.

$$d_i = p \times \frac{M - (z_i - 1)}{M - 1}, \tag{2}$$

$$\boldsymbol{X}_i(t + 1) = \boldsymbol{X}_i(t) + d_i \cdot rand[0, 1] \cdot (\boldsymbol{X}_{Gbest} - \boldsymbol{X}_i(t)), \tag{3}$$

where the parameter d_i is pheromone strength. The value of d_i becomes so small that ranking goes to a low rank, and the strength of a pheromone also becomes weak. where the parameter p is positive acceleration coefficient.

Step. 8 PBHCO let $t = t+1$. PBHCO goes back to [Step. 3], and repeats until $T = t$.

III. SIMULATION

A. Benchmark Functions

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

1. Sphere function :

$$f_1(x) = \sum_{d=1}^{D} x_d^2, \tag{4}$$

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

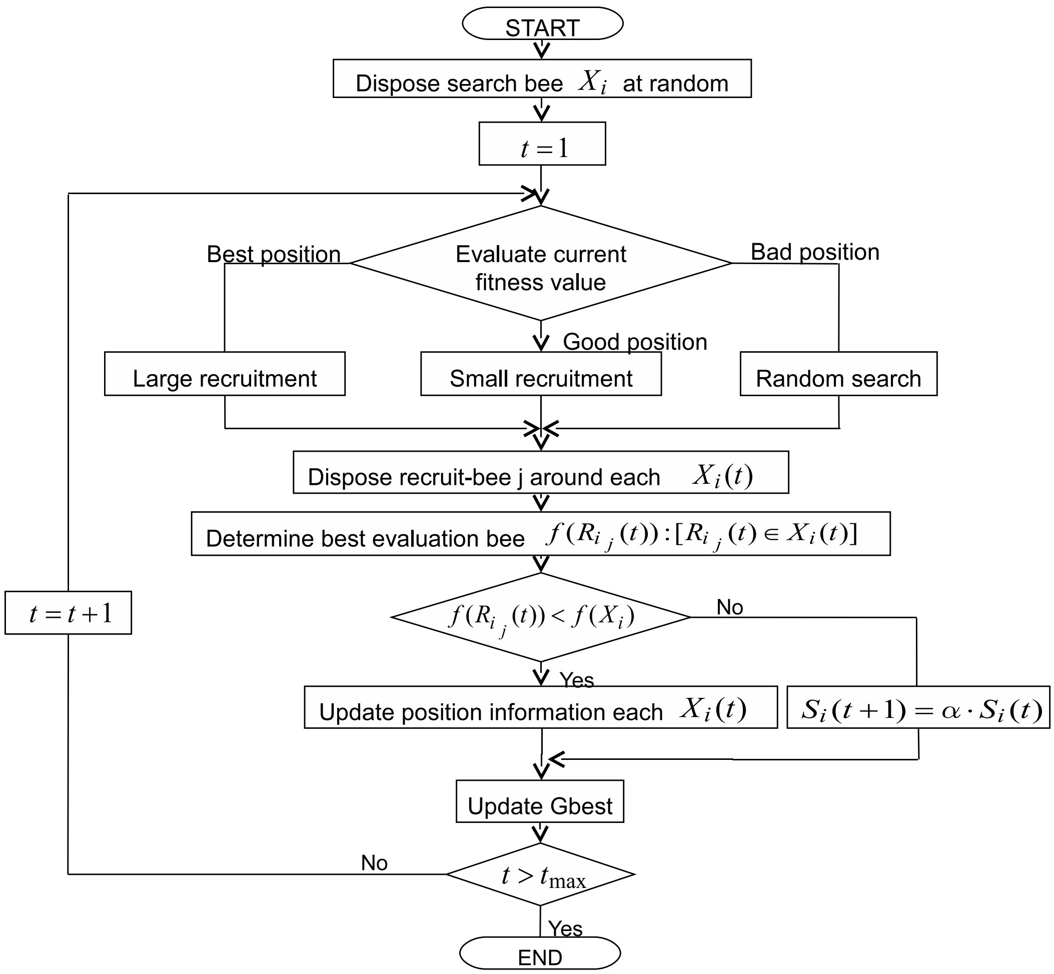

Fig. 2. Flowchart of PBHCO algorithm.

2. Rosenblock function :

$$f_2(x) = \sum_{d=1}^{D-1}(100(x_{d+1}^2 - x_d)^2 + (x_d - 1)^2), \tag{5}$$

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

3. Rastrigin function :

$$f_3(x) = 10D + \sum_{d=1}^{D}(x_d^2 - 10\cos(2\pi x_d)), \tag{6}$$

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

4. Stretched V sine wave function :

$$f_4(x) = \sum_{d=1}^{D-1}((x_d^2 + x_{d+1}^2)^{0.25}(1 + \sin(50(x_d^2 + x_{d+1}^2)^{0.1})^2, \tag{7}$$

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

The functions f_1 and f_2 are unimodal functions which have a peak, f_3 and f_4 are multimodal functions which have many peak in the solution space. Then, in the case of multimodal functions, the solution tend to fall into local minima easily than unimodal functions. All the functions have the dimension parameter D. In this study, D is set 30 and 100 to investigate the performance for different dimensions. We carry out the simulation 100 times with 2000 generations.

B. Simulation Results

First, we carry out different values of p in order to suitable p value. We choose the four functions with $D = 30$ for this experiment. The results are shown in Table I. From this table, we can see that PBHCO obtains best performance for all problems, when p is set to 0.45. Hence we use $p = 0.45$ for the following experiments.

Next, in order to evaluate the performance of PBHCO, we compare the three algorithms; HCO, PBHCO, and par-

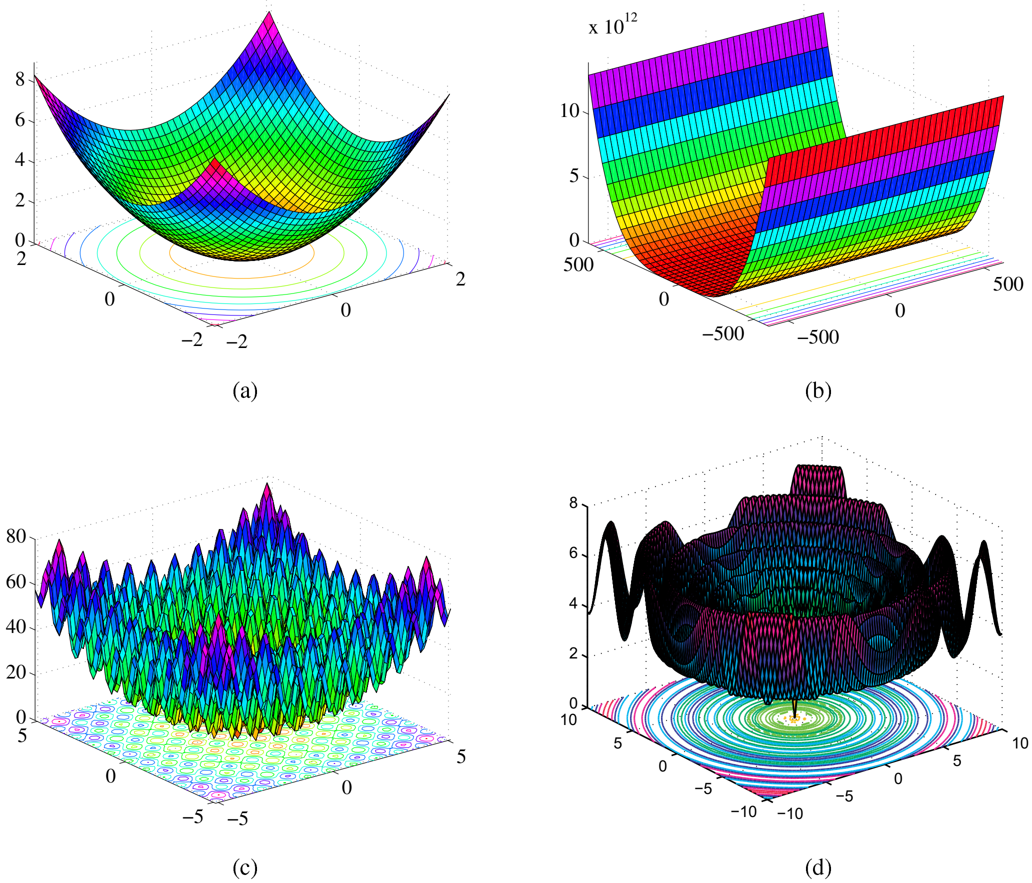

Fig. 3. Landscape of four bench marks for $D = 2$. (a) Sphere function. (b) Rosenblock function. (c) Rastrigin function. (d) Stretched V sine wave function.

TABLE I
Comparison of three kinds parameters p with $D = 30$.

f		$p = 0.1$	$p = 0.45$	$p = 1.0$
f_1	Avg.	3.90e-061	**6.60e-068**	1.53e-057
	Min.	2.56e-063	2.43e-069	1.05e-059
	max.	1.72e-060	2.58e-067	5.14e-057
f_2	Avg.	26.84	**26.41**	27.16
	Min.	23.15	25.61	22.90
	max.	29.39	29.40	29.39
f_3	Avg.	259.72	**43.38**	58.40
	Min.	222.59	30.84	31.84
	max.	299.95	60.69	89.55
f_4	Avg.	54.34	**34.70**	44.55
	Min.	45.16	26.51	40.48
	max.	63.76	41.03	48.06

ticle swarm optimization (PSO) [4]. HCO is the standard HCO method which does not use pheromone. PBHCO is the proposed algorithm explained in Section II. PSO is popular optimization method for the solution of object function, and has the character of the pheromone similar to PBHCO. The parameters of HCO are set as follows;

$$M = 31, b = 2, e = 5, N_1 = 8, N_2 = 4, S_i = 1.75, \alpha = 0.95$$

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 good sites.

The parameters of PBHCO are set as follows;

$$M = 31, b = 1, e = 17, N_1 = 13, N_2 = 2, z_i = 0.02, S_i = 1.70, \alpha = 0.9.$$

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 HCO and PBHCO.

The result for the 30 dimensional functions are summarized in Table II.

For f_1 and f_3, PBHCO can obtain the best results. However, PSO obtains the best result for f_2 and f_4. And, PBHCO and HCO shows the similar performance. This is because that PSO is effective for a low dimension problem, and converge with high speed in unimodal function which has one peak.

Figure 4 shows the simulation result of 100 average of three optimization algorithms. From Fig. 4, the convergence speed of PBHCO is similar to the other two methods. We consider

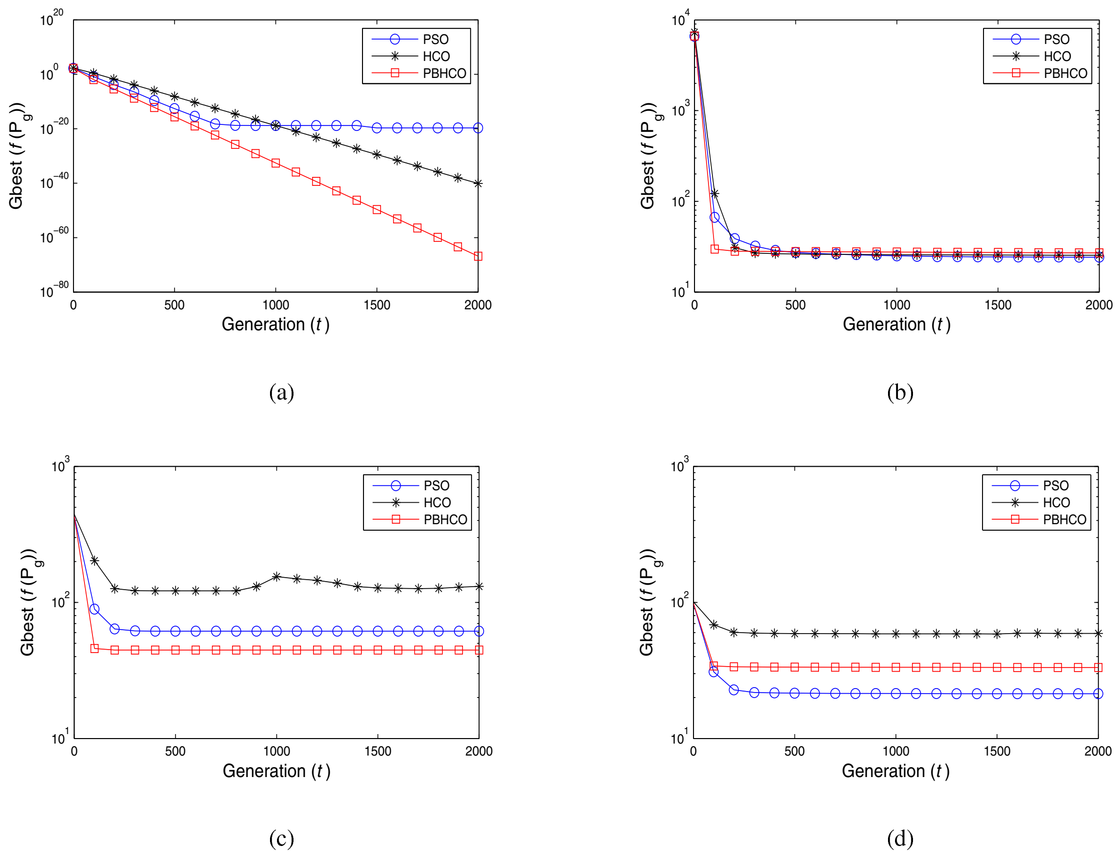

Fig. 4. Average *Gbest* value of every generation for 30-dimensional four functions. (a) Sphere function. (b) Rosenblock function. (c) Rastrigin function. (d) Stretched V sine wave function.

TABLE II
Comparison of PSO, HCO and PBHCO results with D = 30.

f		PSO	HCO	PBHCO
f_1	Avg.	2.00e-020	7.76e-041	**1.38e-067**
	Min.	3.68e-063	4.64e-042	6.59e-071
	max.	2.00e-018	7.64e-040	2.56e-066
f_2	Avg.	**24.20**	25.44	27.00
	Min.	4.01	12.08	23.89
	max.	76.24	29.30	29.40
f_3	Avg.	61.47	131.36	**44.72**
	Min.	27.86	86.56	19.90
	max.	118.40	173.12	91.54
f_4	Avg.	**21.30**	59.13	33.24
	Min.	9.23	47.10	22.72
	max.	38.03	68.19	56.83

TABLE III
Comparison of PSO, HCO and PBHCO results with D = 100.

f		PSO	HCO	PBHCO
f_1	Avg.	0.22	1.42e-014	**4.97e-021**
	Min.	2.50e-007	1.98e-015	5.12e-022
	max.	4.31	5.41e-014	5.26e-020
f_2	Avg.	190.96	113.65	**97.41**
	Min.	75.53	89.50	93.56
	max.	369.44	205.31	98.70
f_3	Avg.	466.14	717.97	**134.34**
	Min.	302.43	554.19	77.61
	max.	630.81	856.06	230.83
f_4	Avg.	203.08	252.71	**141.48**
	Min.	160.66	232.71	121.20
	max.	245.43	267.08	162.47

that the action of the pheromone of PBHCO is not effective for the low dimensional problems.

Next, the result for the 100 dimensional functions are summarized in Table III. The performances of PBHCO 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. Figure 5 shows the simulation result of 100 average for 1000-dimensional functions. From these results, we can see that PBHCO is the effective algorithm for the high dimension problems and multimodal functions.

IV. Conclusion

In this study, we have proposed Pheromone-Based Honeybee Colony Optimization (PBHCO) and have confirmed that the PBHCO could obtain the effective results especially

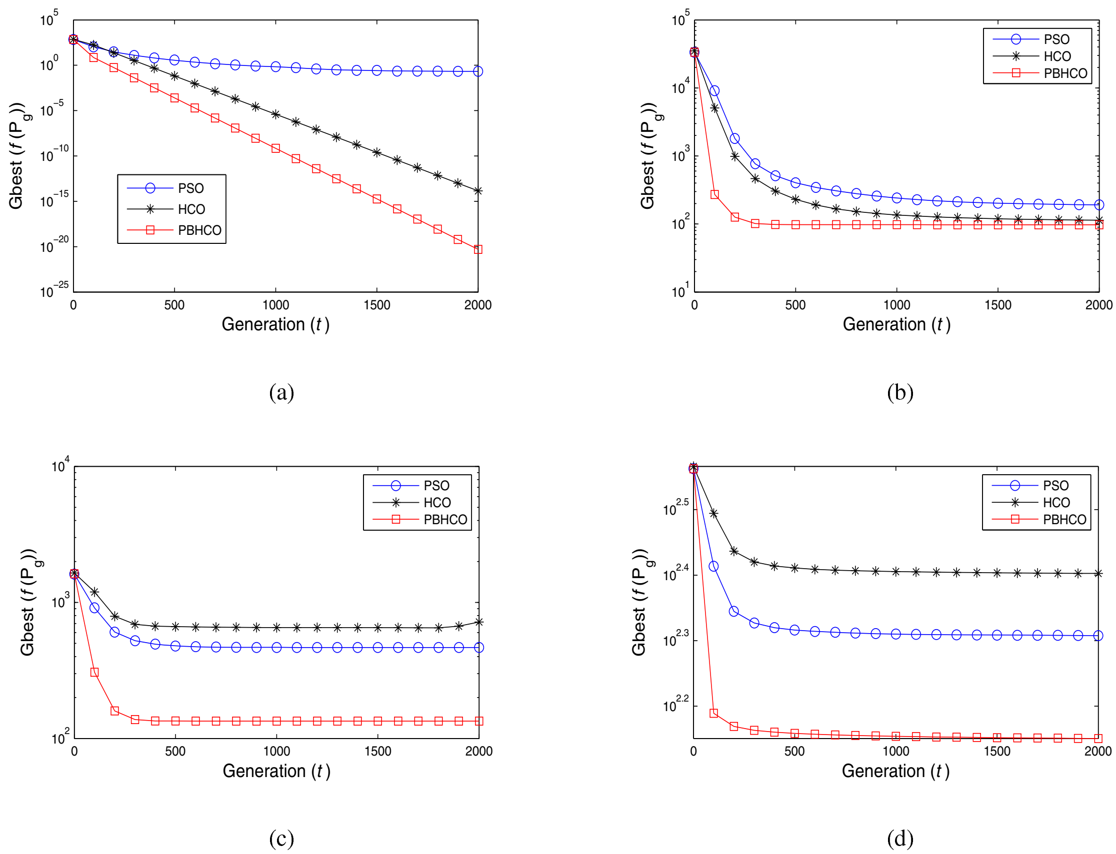

Fig. 5. Average *Gbest* value of every generation for 100-dimensional four functions. (a) Sphere function. (b) Rosenblock function. (c) Rastrigin function. (d) Stretched V sine wave function.

for two functional optimization problems in used function approximation. A pheromone has an effect to attract the other bee to the food source. By computer simulations, we have confirmed that PBHCO was able to converge to the optimal solution with high speed by escaping from local minima. Especially, the pheromone is more effective for higher dimensional and multimodal functions. In future works, we investigate the performance of PBHCO when different types of pheromones are used.

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