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An enhanced hybridized artificial bee colony algorithm for optimization problems

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ABSTRACT

Artificial bee colony (ABC) algorithm is a popular swarm intelligence based algorithm. Although it has been proven to be competitive to other population-based algorithms, there still exist some problems it cannot solve very well. This paper presents an Enhanced Hybridized Artificial Bee Colony (EHABC) algorithm for optimization problems. The incentive mechanism of EHABC includes enhancing the convergence speed with the information of the global best solution in the onlooker bee phase and enhancing the information exchange between bees by introducing the mutation operator of Genetic Algorithm to ABC in the mutation bee phase. In addition, to enhance the accuracy performance of ABC, the opposition-based learning method is employed to produce the initial population. Experiments are conducted on six standard benchmark functions. The results demonstrate good performance of the enhanced hybridized ABC in solving continuous numerical optimization problems over ABC GABC, HABC and EABC.

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1. INTRODUCTION

Recently, many swarm-bsed algorithms have been proposed, including genetic algorithm (GA) [1], particle swarm optimization algorithm (PSO) [2], ant colony optimization algorithm (ACO) [3], differential evolution algorithm (DE) [4], harmony search algorithm (HS) [5], artificial bee colony algorithm (ABC) [6]. ABC proposed by Karaboga is one of the most popular swarm-based algorithms, which is based on the intelligent foraging behavior of honey bee swarm. For the reason that it is simple and easy to implement, ABC algorithm has attracted a lot of scholars' attention. Benchmark functions experiment has shown that ABC is competitive over GA, DE and PSO algorithm. Since proposed, ABC has been widely used in optimization problems.

However, like other swarm algorithms, original ABC algorithm also has some drawbacks in some cases. For example, the solution search equation of original ABC algorithm is good at exploration but not good at exploitation, which results in the poor convergence [7]. To improve ABC's performance, plenty of variant ABC algorithms have been proposed. Search equation is one of the active research trends. Some researchers integrated ABC with several concepts, which were related to evolutionary optimization algorithms. Inspired by PSO, Gbest-guided ABC algorithm, which incorporated the information of global best (gbest) solution into the solution search equation, was proposed by Zhu and Kwong [7]. Tuba et al. proposed a method which integrated self-adaptive guidance adjusted with ABC for engineering optimization problems in [8]. Inspired by DE, an novel solution search equation for ABC, which improves the exploitation process based on that the artificial bee searches only around the best solution of the previous iteration, was proposed in [9]. Karaboga proposed a quick ABC (qABC) algorithm which modeled the behavior of foragers of artificial bee colony more accurately and improved the performance of ABC algorithm in terms of local search ability [10]. Inspired by GA, TRAN Dang Cong et al. proposed a novel hybrid data clustering algorithm based on artificial bee colony algorithm by incorporating the solution search equation of GABC and proposing a mutation operation to improve the algorithm both in exploitation and exploration abilities, and make the algorithm be capable to avoid local optima [11]. Gao Wei-feng et al. proposed an inspired artificial bee colony algorithm (IABC), in which the bee searches around the best solution of the previous iteration to improve the exploitation and the opposition-based learning method is employed to produce the initial population, for global optimization problems [12]. Another research trend is to combine some traditional and heuristic optimization algorithms with ABC. This type ABC is known as the hybridized ABC. In [13],[14], Nelder-Mead simplex approach was combined with ABC to improve the search efficiency. Bin et al. applied a differential ABC algorithm to solve global numerical optimization problem [15]. Kang et al. proposed a method which combined ABC with Hooke Jeeves pattern search method in [16].

The researchers of this paper noted that the information of global best solution could be used to improve the exploitation and the crossover operation of GA could be combined with ABC to enhance ABC's exploration and exploitation abilities. Hence, an enhanced hybridized ABC algorithm for optimization problems was proposed in this paper. Firstly, opposition-based learning method is employed to generate the initialization population to make use of the search space. Next, a search equation with global best solution is employed in onlooker bee phase to improve the search ability. Finally, a new bee phase called mutation phase, which can improve ABC's exploitation and exploration, is employed. Therefore, the proposed algorithm above can contribute to a more robust and faster method. The efficiency of EHABC was tested by six standard benchmark functions. The rest of the paper is structured as follows. In Section 2, the original ABC algorithm is described. The enhanced hybridized ABC algorithm is introduced in Section 3. The experiment results are conducted and discussed in section 4. In Section 5, the conclusion is given.

2. ARTIFICIAL BEE COLONY ALGORITHM

In oritnal ABC algorithm, the colony of the artificial bees contains three categories: employed bees, onlooker bees and scout bees. A possible solution to the target optimization problem is indicated by the position of a food source, and the fitness of the associated solution represents the nectar amount of each food source. The number of employed bees equals to the amount of food sources [6].

At the step of initialization, ABC generates a distributed initial population of SN food sources (solutions), where SN denotes the amount of employed bees (or onlooker bees) and equals to half of the colony size. Each initial solution $X_i = \{x_{i,1}, x_{i,2}, \dots, x_{i,D}\}$ is generated randomly within the range of the search space of the parameters using Eq. (1) as follow:

$$x_{i,j} = x_{min,j} + rand(0,1)(x_{max,j} - x_{min,j}) \tag{1}$$

Where $i = 1, 2, \dots, SN$,and $j = 1, 2, \dots, D$. D indicates the dimension of optimization problems; $x_{max,j}$ and $x_{min,j}$ are the upper and lower bounds for the dimension j, respectively.

In the repeated cycles of the search, task of searching a new food source is assigned to every employed bee and onlooker bee. To generate a candidate food source V_i from the old position X_i, ABC uses Eq. (2) as follow:

$$v_{i,j} = x_{i,j} + \emptyset_{i,j}(x_{i,j} - x_{k,j}) \tag{2}$$

Where $k \in \{1, 2, \dots, SN\}$ and $j \in \{1, 2, \dots, D\}$ are randomly selected indexes; k must be different from i, and $\emptyset_{i,j}$ is a number randomly selected in the range $[-1, 1]$. An onlooker bee selects a food source according to the probability value p_i, which is associated with the food source, using Eq. (3) and Eq. (4) as follow:

$$p_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_j} \tag{3}$$

$$fit_i = \begin{cases} 1/(1 + f_i)\,, if\ f_i \geq 0 \\ 1 + abs(f_i), otherwise \end{cases} \tag{4}$$

Where $\mathrm{fit_i}$ indicates the fitness value of solution i, $\mathrm{f_i}$ represents the objective function value of solution $\mathrm{x_i}$ and $\mathrm{j} = 1, 2, \dots, \mathrm{D}$. In this way, the employed bees can exchange information with the onlooker bees. Once a solution cannot be improved further through the predefined number of cycles called limit, this food source will be abandoned. The abandoned source is set to be $\mathrm{X_i}$. Then the scout bee produces a new food source randomly as in Eq.(1) to replace with $\mathrm{X_i}$.

3. ENHANCED HYBRIDIZED ARTIFICIAL BEE COLONY ALGORITHM

Many researches showed that the original ABC is poor at exploitation because the initialization population and candidate solutions in the onlooker phase are produced randomly without using other information, such as global best solution [11]. Aim to improve the performance of standard ABC, this paper presents a new approach by employment of opposition-based learning method, improved onlooker bee search equation with the information of global best solution, and mutation operation.

3.1. Initial Population Using Opposition-based Learning Method

Initialing population with random method may not go through the whole search space that it will decrease the fine search ability and cause premature convergence problem. This paper generates the initial population with the opposition-based learning method to avoid premature convergence [17]. Firstly, generate initial population randomly; then generate opposition solutions for every initial population position; Finally, select SN solutions with better fitness from the two initial populations produced above to conduct the EHABC's initial population. Opposition-based learning method is defined as Algorithm 1.

Algorithm 1 Initial Population Using Opposition-based Learning Method

Initialize population size SN, dimension D, the maximum number of function evaluations, $Max.FE$ and $limit$;
for $i = 1$ *to* SN **do**
  for $j = 1$ *to* D **do**
    $x_{i,j} = x_{min,j} + rand(0,1)(x_{max,j} - x_{min,j})$
  end
end
for $i = 1$ *to* SN **do**
  for $j = 1$ *to* D **do**
    $ox_{i,j} = x_{min,j} + x_{max,j} - x_{i,j}$
  end
end
Select SN solutions with better fitness from $X(SN) \bigcup OX(SN)$ as the initial population;

3.2. Improved Onlooker Bee Search Equation

Inspired by PSO algorithm, an improved ABC algorithm called GABC algorithm was proposed in [7]. To improve the exploitation ability of standard ABC, GABC makes use of the information of global best solution in the solution search equation using Eq. (5) as follows [7].

$$v_{i,j} = x_{i,j} + \emptyset_{i,j}\left(x_{i,j} - x_{k,j}\right) + \varphi_{i,j}(x_{best,j} - x_{i,j}) \tag{5}$$

Where $\mathrm{x_{best,j}}$ is the jth element of the global best solution, $\varphi_{\mathrm{i,j}}$ is a uniform random number in $[1, 1.5]$.

However, Wei-feng Gao et al. pointed out that since the guidance of the last two terms of Eq. (3.1) may be in opposite directions, it might cause an "oscillation" phenomenon, which would cause inefficiency to the search ability of GABC and delay convergence [18]. Hence, this paper employed the well-modified search equation to avoid this phenomenon, which would benefit the performance of ABC, as Eq. (6) shows.

$$v_{i,j} = x_{k,j} + rand(0,1)(x_{best,j} - x_{k,j}) \tag{6}$$

Where k is an integer randomly select from the range $[1, \mathrm{SN}]$ and is also different from i, and $\mathrm{X_{best}}$ is the best solution with best fitness in the current population. With the guidance of the only one term $(\mathrm{x_{best,j}} - \mathrm{x_{k,j}})$ and with $\mathrm{X_{best}}$, Eq.(6) can avoid the oscillation phenomenon, whilst enhances the search ability of ABC. By the way, since the vector $\mathrm{X_k}$ for generating the candidate solution is chosen from the population randomly and consequently, it doesnt' have bias to any special search directions, therefore, Eq.(6) can try to keep the exploration.

3.3. Mutation Bee Phase

[19] proposed an approach called HABC by incorporating arithmetic crossover method of GA with ABC. Inspired by the mutation operation of DE and the crossover operation of HABC, TRAN Dang Cong et al. proposed a new approach to update the position of individual in mutation bee phase using Eq. (3.3), where the information of global best solution was employed to further improve the performance of ABC [11]. In this paper, Eq. (7) is also applied to the candidate solution search equation of EHABC's mutation bee phase. The search equation in mutation bee phase is modeled as Eq. (7).

$$v_{i,j} = rand(0,1) \cdot \left(x_{i,j} - x_{k_1,j}\right) + rand(0,1) \cdot (x_{best,j} - x_{k_2,j}) \tag{7}$$

Where $x_{k_1,j}$ and $x_{k_2,j}$ are two food positions that are chosen from food source population randomly. i, k_1 and k_2 are mutually different, and x_{best} is the global best solution. With this mutation operation, the global best solution and current individual, and two randomly chosen individuals not only improve the original ABC's exploitation and exploration abilities, but also make the algorithm be able to avoid local optima.

By applying three methods introduced above, the main steps of EHABC proposed are described in Algorithm 2, where the termination condition is met when the number of Function evaluations (FEs) reaches the predetermined Maximum number ($Max.FE$).

```
Algorithm 2 The main steps of EHABC
Initialize the population of employed bees by using Algorithm 1; while FE < Max.FE
do
    for each employed bee do
        Randomly choose a neighbor employed bee;
        Update the position of employed bee by using Eq. 2;
        Calculate the fitness value by using Eq. 4;
        Apply greedy selection strategy;
        Update trial counter of the bee;
    end
    Calculate the probability of each food source by Eq. 3;
    for each onlooker bee do
        Select an employed bee for improvement its solution according to the probability;
        Randomly choose an employed bee as neighbor;
        Generate the candidate solution of the employed bee by using Eq. 6 and the
        neighbor;
        Calculate the fitness value by using Eq. 4;
        Apply greedy selection strategy;
        Update trial counter of the bee;
    end
    /* Mutation bee phase */
    for each food source f_i in food source population do
        Randomly choose two parents different to i from the food source population;
        Generate new food source by Eq. 7;
        Calculate the fitness value by using Eq. 4;
        Apply greedy selection strategy;
        Update trial counter of the bee;
    end
    if there is an employed bee becomes scout then
        replace it with a new random generated source position;
    end
end
```

4. Results and Discussion

The performance of EHABC is evaluated on six well-known standard benchmark functions with 10 dimensions (low dimension) and 50 dimensions (high dimension) over 30 runs, and compared to 4 other ABC variants: canonical ABC [6], GABC [7], HABC [19] and EABC [11]. For a fair comparison, all ABC variants are tested using the same settings of the parameters. When $\mathrm{D} = 10$, the population size $\mathrm{SN} = 40$, $\mathrm{limit} = 200$, and $\mathrm{Max.FE} = 2{,}000$. When $\mathrm{D} = 50$, the population size $\mathrm{SN} = 200$, $\mathrm{limit} = 200$, and $\mathrm{Max.FE} = 100{,}000$. The test problems, range of the search spaces and the global optimum values for the problems are presented in Table 1. The mean values (mean) and standard deviation (SD) values obtained for the low-dimensional and high-dimensional test problems are presented in Table 2 and 3 respectively.

4.1. Results with $\mathbf{D} = 10$

In this section, as seen from the Table 2, EHABC can get best accuracy performance in terms of mean and SD of final values in most cases. Figure 1 shows the convergence graphics of these five ABC variants for test problems. For all problems, it can be concluded that EHABC is quicker than the other ABC variants. Therefore, the experiment results and comparisons verify that EHABC improves both the accuracy and the local convergence performance of original ABC on low-dimensional functions.

Table 1. Test problems

Name	Function	Interval	Global Optimum
Sphere	$f_1(X) = \sum_{i=1}^{n} x_i^2$	$[-100, 100]$	$F_{min} = 0$, $X = (0,0,\dots)$
Rosenbrock	$f_2(X) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	$[-30, 30]$	$F_{min} = 0$, $X = (1,1,\dots)$
Rastrigin	$f_3(X) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	$[-5.12, 5.12]$	$F_{min} = 0$, $X = (0,0,\dots)$
Griewank	$f_4(X) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	$[-600, 600]$	$F_{min} = 0$, $X = (0,0,\dots)$
Ackley	$f_5(X) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	$[-32, 32]$	$F_{min} = 0$, $X = (0,0,\dots)$
Schwefel	$f_6(X) = 418.98288727243369 * n - \sum_{i=1}^{n} x_i \sin(\sqrt{\lvert x_i \rvert})$	$[-500, 500]$	$F_{min} = 0$, $X = (420.9687,420.9687,\dots)$

Table 2. Performance comparison of five ABC variants with $D = 10$

Function		ABC	GABC	HABC	EABC	EHABC
f_1	Mean	8.47663e-17	5.57133e-17	4.19697e-18	5.23848e-17	3.49592e-18
	SD	2.34869e-17	1.44997e-17	2.41693e-18	1.8038e-17	2.22565e-18
f_2	Mean	0.404502	0.0905165	0.176567	0.0379949	0.0691254
	SD	0.678632	0.19784	0.430975	0.0506429	0.183442
f_3	Mean	0	0	0	0	0
	SD	0	0	0	0	0
f_4	Mean	0.00277328	0.00174731	0.000282161	0.000271158	7.31267e-15
	SD	0.00501418	0.00360317	0.00154546	0.00148519	4.00531e-14
f_5	Mean	7.87518e-15	6.69094e-15	2.42769e-15	5.50671e-15	4.67774e-15
	SD	1.13631e-15	1.7413e-15	1.79059e-15	1.65589e-15	9.01352e-16
f_6	Mean	-8.18545e-13	-9.09495e-13	-6.36646e-13	-8.79178e-13	-5.76013e-13
	SD	2.77513e-13	0	4.23908e-13	1.6605e-13	4.45773e-13

Table 3. Performance comparison of five ABC variants with $D = 50$

Function		ABC	GABC	HABC	EABC	EHABC
f_1	Mean	8.06772e-16	5.80662e-16	2.04745e-17	5.85847e-16	4.24218e-21
	SD	6.87937e-17	6.4833e-17	2.48142e-18	5.93146e-17	1.75257e-21
f_2	Mean	0.00140859	9.88673e-05	0.00180016	0.000215487	7.34871e-05
	SD	0.00138648	5.07455e-05	0.00136541	0.000139003	7.34777e-05
f_3	Mean	0	0	0	0	0
	SD	0	0	0	0	0
f_4	Mean	5.92119e-17	0	0	0	0
	SD	5.63345e-17	0	0	0	0
f_5	Mean	6.44818e-14	4.89682e-14	2.16123e-14	4.55339e-14	2.80072e-14
	SD	3.65536e-15	3.19585e-15	1.88531e-15	2.90328e-15	4.1182e-15
f_6	Mean	1.09139e-11	1.09139e-11	1.74623e-11	1.09139e-11	1.11565e-11
	SD	0	0	1.76163e-12	0	1.3284e-12

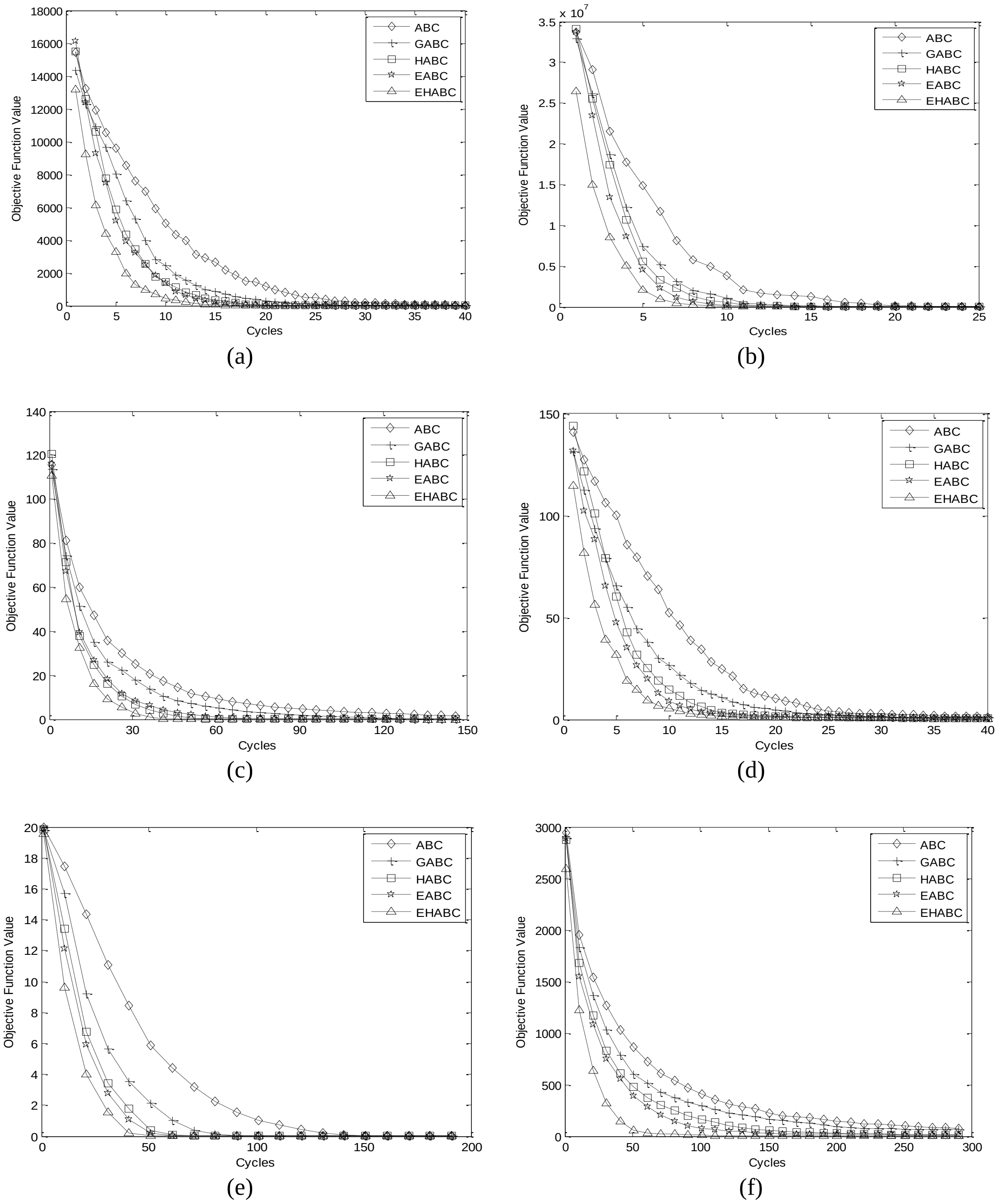

Figure 1. Convergence performance of different ABCs on (a) Sphere, (b) Rosenbrock, (c) Rastrigin, (d) Griewank, (e) Ackley, (f) Schwefel function with $D = 10$

4.3. Discussion

Through the similation on six benchmark functions with 10D and 50D, the results show that EHABC has better performance than other four ABC variants on the majority of test functions. EHABC has the fastest convergence speed on all test functions, but it is trapped into local optima on few functions. EHABC obtained these results because three main reasons: 1) More uniformly distributed initial population with opposition-based learning method; 2) Each candidate solution in the onlooker bee phase learns from the global best solution and a randomly selected solution, that improves the exploration ability; 3) What's more, in the mutation bee phase, each candidate solution learns from itself and global best solution that promotes the exploitation ability and enhances the exploration ability of the algorithm respectively.

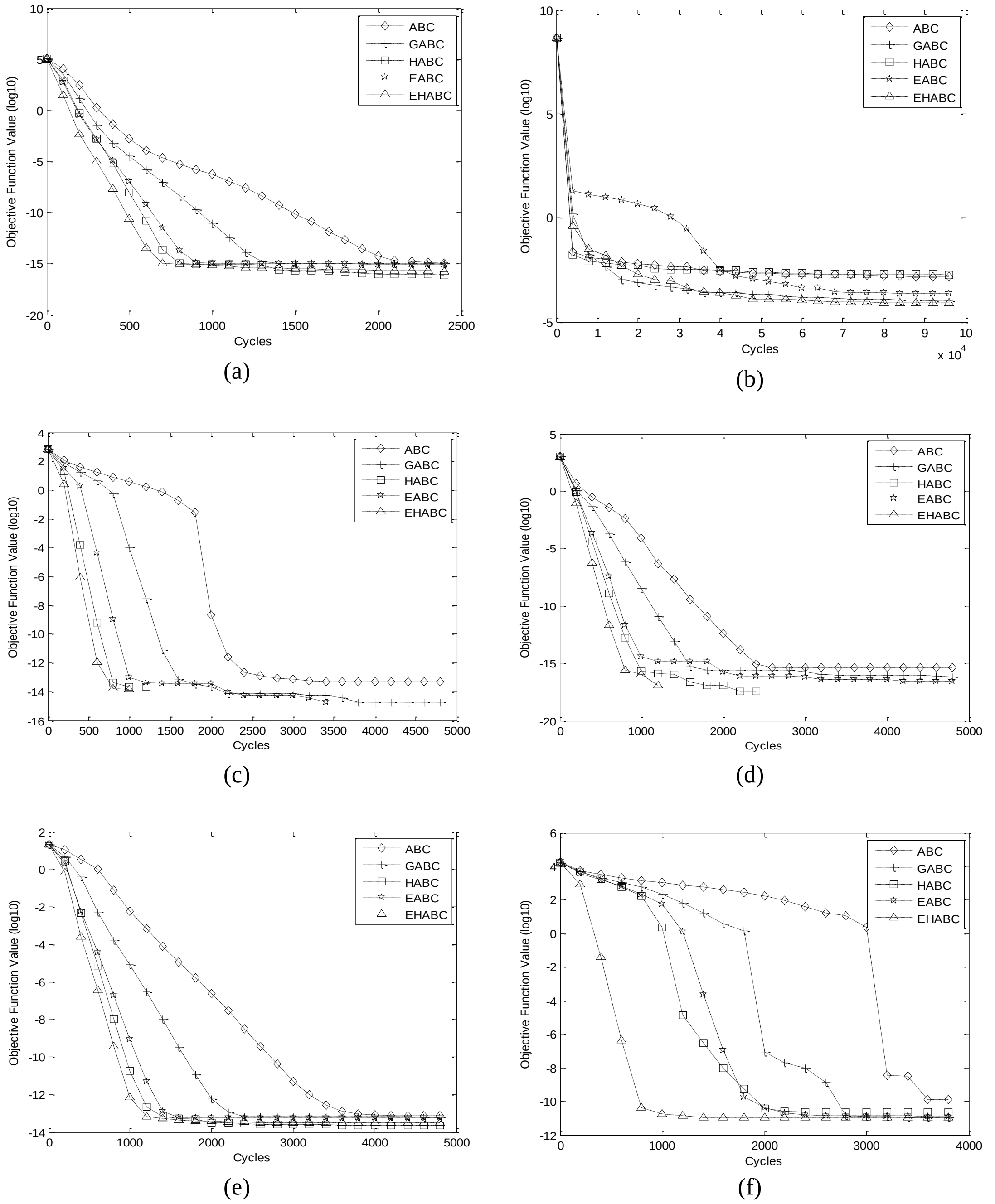

Figure 2. Convergence performance of different ABCs on (a) Sphere, (b) Rosenbrock, (c) Rastrigin, (d) Griewank, (e) Ackley, (f) Schwefel function with $D = 50$

5. CONCLUSION

This paper proposed a new approach EHABC in order to enhance the original ABC algorithm for global optimization problem. ABC, GABC, HABC, EABC and EHABC algorithms were tested on six standard benchmark functions and results obtained were compared. Experiment results showed that, by combining opposition-based learning method, well-designed onlooker bee search equation and mutation bee phase, EHABC get better exploitation and exploration abilities than the other four ABC variants, and improves original ABC both in terms of accuracy and convergence speed. In the future, the researchers of this paper will extend the research for the aim of applying EHABC to practical applications, such as public opinion trends prediction problem [20].

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