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An Improved Artificial Bee Colony Algorithm for Global Optimization

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Abstract: To improve the performance of Artificial Bee Colony algorithm (ABC), an Improved ABC (IABC) for global optimization was proposed with the opposition-based initialization method. Inspired by particle swarm optimization algorithm and differential evolution algorithm, a new search mechanism was also developed to balance the exploration and exploitation abilities. The algorithms was applied to 4 benchmark function with effects of selective probability p. To verify the performance of IABC algorithm, 10 benchmark functions were tested with various dimensions. Numerical results demonstrated the proposed algorithms outperformed the ABC in global optimization problems.

Key words: Artificial bee colony algorithm, Oopposition-based initialization method, particle swarm optimization, differential evolution

INTRODUCTION

Global optimization problems are crucial in almost every field of engineering, science and business managements. By now, many intellegence optimization methods have been developed to solve these problems, such as genetic algorithms (GAs) (Tang *et al*., 1996), Ant colony Optimization (ACO) (Dorigo and Stutzle, 2004), Differential Evolution (DE) (Storn and Price, 1997) and Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995; Tang *et al*., 2010). These kinds of algorithms are constructed by learning from life system, which can also be named as artificial-life computation.

Recently, a new intellegent algorithm was proposed by Karaboga, named Artificial Bee Colony (ABC) algorithm for global numerical function optimization (Karaboga, 2005). In ABC algorithm, the individuals simulate the foraging behavior of honey bee swarm. After that, a set of comparison experiments were tested to show that ABC algorithm is competitive to some conventional bio-inspired algorithms with an advantage of employing fewer control parameters (Karaboga and Akay, 2009; Kang *et al*., 2011; Wu and Qian, 2011). Due to its simplicity, ABC algorithm has been applied to many real-world problems, such as leaf-constrained minimum spanning tree problem (Singh, 2009), flow shop scheduling problem (Pan *et al*., 2011), inverse analysis problem (Kang *et al*., 2009), radial distribution system network reconfiguration problem (Rao *et al*., 2008), clustering problem (Zhang *et al*., 2010), TSP problems (Hu and Zhao, 2009) and so on (Lei and Jing, 2011; Hirzallah, 2011; Zhang *et al*., 2012).

Recently, a new intellegent algorithm was proposed by Karaboga, named artificial bee colony (ABC) algorithm for global numerical function optimization (Karaboga, 2005). In ABC algorithm, the individuals simulate the foraging behavior of honey bee swarm. After that, a set of comparison experiments were tested to show that ABC algorithm is competitive to some conventional bio-inspired algorithms with an advantage of employing fewer control parameters (Karaboga and Akay, 2009; Kang *et al*., 2011; Wu and Qian, 2011). Due to its simplicity, ABC algorithm has been applied to many real-world problems, such as leaf-constrained minimum spanning tree problem (Singh, 2009), flow shop scheduling problem (Pan *et al*., 2011), inverse analysis problem (Kang *et al*., 2009), radial distribution system network reconfiguration problem (Rao *et al*., 2008), clustering problem (Zhang *et al*., 2010), TSP problems (Hu and Zhao, 2009) and so on (Lei and Jing, 2011; Hirzallah, 2011; Zhang *et al*., 2012).

According to the above disccusions, ABC algorithm seems to be a well-performed algorithm. However, similar to other population-based algorithms, there still have some drawbacks in ABC algorithm, such as slower convergence speed for some unimodal problems and easily get trapped in local optima for some complex multimodal problems, because the search equation of ABC algorithm is good at exploration but poor in exploitation. It is well known that for the population-based algorithms the exploration and the exploitation abilities are both necessary facts. The exploration ability refers to the

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ability to investigate the various unknown regions to discover the global optimum in solution space, while the exploitation ability refers to the ability to apply the knowledge of the previous good solutions to find better solutions. The exploration ability and the exploitation ability contradict to each other, so that the two abilities should be well balanced to achieve good performance.

Therefore, accelerating convergence speed and avoiding local optima have become two most important goals in ABC algorithm modification. To achieve the two goals above, inspired by PSO and DE, a new search mechanism is proposed in the Improved Artificial Bee Colony (IABC) algorithm. In order to balance the exploration ability and the exploitation ability, a selective probability p is introduced to control the frequency of introducing "G-best" and"ABC/best/2". In addition, to enhance the convergence speed, the opposition-based initialization is employed. Experimental results denote the effectiveness and efficiency of IABC algorithms.

The rest of the paper is organized as follows. In Section 2, ABC algorithm is summarized briefly and the proposed improved artificial bee colony algorithm is described. In Section 3, experiments are presented and the results are discussed. Finally, a conclusion is provided.

PROPOSED SCHEME

Artificial bee colony algorithm: In ABC algorithm, the colony consists of three kinds of bees: employed bees, onlooker bees and scout bees. Half of the colony is employed bees and the other half is onlooker bees. The employed bees explore the food source and send the information of the food source to the onlooker bees. The onlooker bees choose a food source to exploit based on the information shared by the employed bees. The scout bee, which is one of the employed bees whose food source are abandoned, finds a new food source randomly. The position of a food source is a possible solution to the optimization problem. Denote the food source number as SN, the position of the ith food source as x_i (i = 1, ..., SN), which is a D-dimensional vector.

A candidate solution from the old one can be generated as:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \quad (1)$$

wherem k∈{1, 2, ..., SN}, k≠i and j =∈{1, 2, .., D} are randomly selected indices, ϕ_{ij}∈[-1, 11] is a uniformly distributed random number. The candidate solution is compared with the old one and the better one should be remained.

In ABC algorithm, the ith fitness value fit_i for a minimization problem is defined as:

$$fit_i = \begin{cases} \frac{1}{1+f_i}, & f_i \geq 0, \\ 1+abs(f_i), & f_i < 0, \end{cases} \quad (2)$$

where, f_i is the cost value of the ith solution.

The probability of a food source being selected by an onlooker bee is given by:

$$p_i = \frac{fit_i}{\sum_{i=1}^{SN} fit_i} \quad (3)$$

If the abandoned food source is x_i, the scout bee exploits a new food source according to:

$$X_{ij} = x_j^{min} + rand(0, 1)\,(x_j^{max} - x_j^{min}) \quad (4)$$

where, x_j^{max} and x_j^{min} are the upper and lower bounds of the jth dimension of the problem's search space.

Opposition-based learning initialization: Population initialization is a crucial task in evolutionary algorithms, because it can affect the convergence speed and the quality of the final solution. If no information about the solution is available, then random initialization is the most commonly used method to generate initial population. According to Rahnamayan (Rahnamayan *et al.*, 2008), the opposition-based population initialization can get better initial solutions and accelerate convergence speed. So, this paper employs the opposition-based learning method to generate initial population. The initial population is generated as follows:

$$ox_{ij} = x_j^{min} + x_j^{max} - x_{ij} \quad (5)$$

Where:

$$x_{ij} = x_j^{min} + rand(0,1)\left(x_j^{max} - x_j^{min}\right)$$

New search mechanism: It is well known that both the exploration and exploitation abilities are necessary for the population based algorithms. How to balance these two abilities to achieve good optimization performance is very important.

Zhu and Sam (2010) inspired by PSO, which in order to improve the exploitation, takes advantage of the information of the global best (G-best) solution to guide the search of candidate solutions, he modify the solution search equation described as follows:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) + \varphi_{ij}(y_j - x_{ij}) \quad (6)$$

where, $k \in \{1, 2, .., SN\}$ is a random selected index which is different from i, $j \in \{1, 2, .., D\}$ is a random selected index, y_i is the jth element of the global best solution, $\phi_{ij} \in [-1, 1]$ and $\phi_{ij} \in [0, 1.5]$ are both uniformly distributed random numbers. The new search mechanism is good at exploration abilities, but is poor at exploitation abilities.

In order to further improve the exploitation abilities, inspired by DE, we proposed new search mechanism named ABC/best/2 described as followed:

$$V_{ij} = x_{best,j} + F(x_{ij} + x_{r1,j} - x_{r2,j} - x_{r3,j}) \quad (7)$$

where, $r_1, r_2, r_3 \in \{1, 2, .., SN\}$ is a random selected index which is different from i and $r_1 \neq r_2 \neq r_3$, $j \in \{1, 2, \ldots, D\}$ is a random selected index, $x_{best,j}$ is the jth element of the global best solution, $F \in [0.5, 1]$ is uniformly distributed random number. Similar to DE, the solution search equation "ABC/best/2" which utilizes the information of the best solutions in the current population can improve the convergence performance but may lead to the premature convergence, especially when solving multimodal problems. In Eq. 6, which takes advantage of the information of global best solution to guide the search of new candidate solutions in order to improve the exploitation, but is not good at exploration abilities to "ABC/best/2". So, we use a selective probability p to control the frequency of introducing "G-best" and "ABC/best/2".

Improved artificial bee colony algorithm: Based on the above analysis, the main steps of the improved artificial bee colony are as follows.

Algorithm (Improved artificial bee colony algorithm):

- Initialize population size SN, the maximum number of evaluations Max.FE
- Initialize the food sources by using the opposition-based learning initialization and evaluate the population, $trail_i = 0$, $(i = 1, 2, \ldots, SN)$. Cycle = 1
- While (FE<*Max.FE*) do
- for *i=1* to *SN* do
- Selected x_k from the current population, where $k \in \{1, 2, \ldots, SN\}$ is a random index which is different from i
- Select j, $j \in \{1, 2, .., \}$ is a random index,
- According to (6), Generate candidate solutions.
- If $f(v_i)<f(x_i)$, then
- $x_i = v_i$
- Else then
- If rand(0,1)<P then
- Select $r_1, r_2, r_3, r_1, r_2, r_3 \in \{1, 2, \ldots, SN\}$ is a random index which is different from i and $r_1 \neq r_2 \neq r_3$, $j \in \{1, 2, .., D\}$ is a random selected index, $F \in [0.5, 1]$
- According to (7), generate candidate solutions
- if $f(v_i)<f(x_i)$, then
- $x_i = v_i$
- End if
- End if
- End if
- End for
- End while (FE=Max.FE)

SIMULATION RESULTS

Test functions: In this section, the IABC algorithm is applied to minimize 10 benchmark functions, as shown in Table 1. All the benchmark functions, presented in Table 1, include unimodal, multimodal, regular, irregular, separable, non-separable and multidimensional. Initial range, characteristics and formulation of these functions are listed in Table 1.

Effects of selective probability p: In this subsection, we investigate the impact of selective probability p on the new algorithm. Note that the test function Beale, Easom, Six Hump Camel Back and Levy are representative, so selective probability p is tested according to these four functions.

The IABC algorithm runs 30 times on each function and the mean values of the final results are plotted in Fig. 1. As all the test functions are minimization problems, the smaller the mean values, the better it is.

From Fig. 1, we can see that the selective probability p can affect the results. For these four test functions, better results are obtained when p is around 0.4. Hence, the selective probability p will be equal to 0.4 for all test functions in the experiments.

Experimental results: In this subsection, a set of experiments tested on 10 benchmark functions were performed, which compared the performance of IABC algorithms with ABC algorithm. The results are shown in Table 2 in terms of best, worst, mean, standard deviation and mean time.

Compared with the results, the mean values of IABC algorithms is equal or close to the optimal ones and the standard deviations are relatively small. IABC algorithm outperforms ABC algorithm on all test functions except function f_2, but its solutions is obtained nearly ABC algorithm. At the mean time, the two algorithms have the same mean function values on function f_5, which equal to the optimal ones. IABC algorithm outperforms ABC

Table 1: Benchmark functions f_1-f_{10} used in experiments. D: Dimension, C: Characteristic, U: Unimodal, M: Multimodal, S: Separable, N: Non-Separable.

No.	Range	D	C	Function	Formulation
1	[-32,32]	30	MN	Ackley	$f(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$
2	[-4.5,4.5]	2	UN	Beale	$f(x) = (1.5 - x_1 + x_1x_2)^2 + (2.25 - x_1 + x_1x_2^2)^2 + (2.625 - x_1 + x_1x_2^3)^2$
3	[-10,10]	2	MS	Booth	$f(x) = (x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2$
4	[-100,100]	2	UN	Easom	$f(x) = -\cos x_1 \cos x_2 \exp(-(x_1 - \pi)^2 - (x_2 - \pi)^2)$
5	[-5,5]	2	MN	Six hump camel back	$f(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$
6	[-10,10]	30	MN	Levy	$f(x) = \sin^2(\pi y_1) + \sum_{i=1}^{n-1}\left[(y_i - 1)^2(1+10\sin^2(\pi y_i + 1))\right] + (y_n - 1)^2(1+10\sin^2(2\pi y_n))$, $y_i = 1 + \frac{x_i - 1}{4}, \quad i = 1,\cdots,n$
7	[-4,5]	4	UN	Powell	$f(x) = \sum_{i=1}^{n/k}(x_{4i-3} + 10x_{4i-2})^2 + 5(x_{4i-1} + 10x_{4i})^2 + (x_{4i-2} + 10x_{4i-1})^4 + 10(x_{4i-3} + 10x_{4i})^4$
8	[-5.12,5.12]	30	MS	Rastrigin	$f(x) = \sum_{i=1}^{n}\left[x_i^2 - 10\cos(2\pi x_i) + 10\right]$
9	[-100,100]	30	US	Sphere	$f(x) = \sum_{i=1}^{n} x_i^2$
10	[-10,10]	30	US	SumSquares	$f(x) = \sum_{i=1}^{n} ix_i^2$

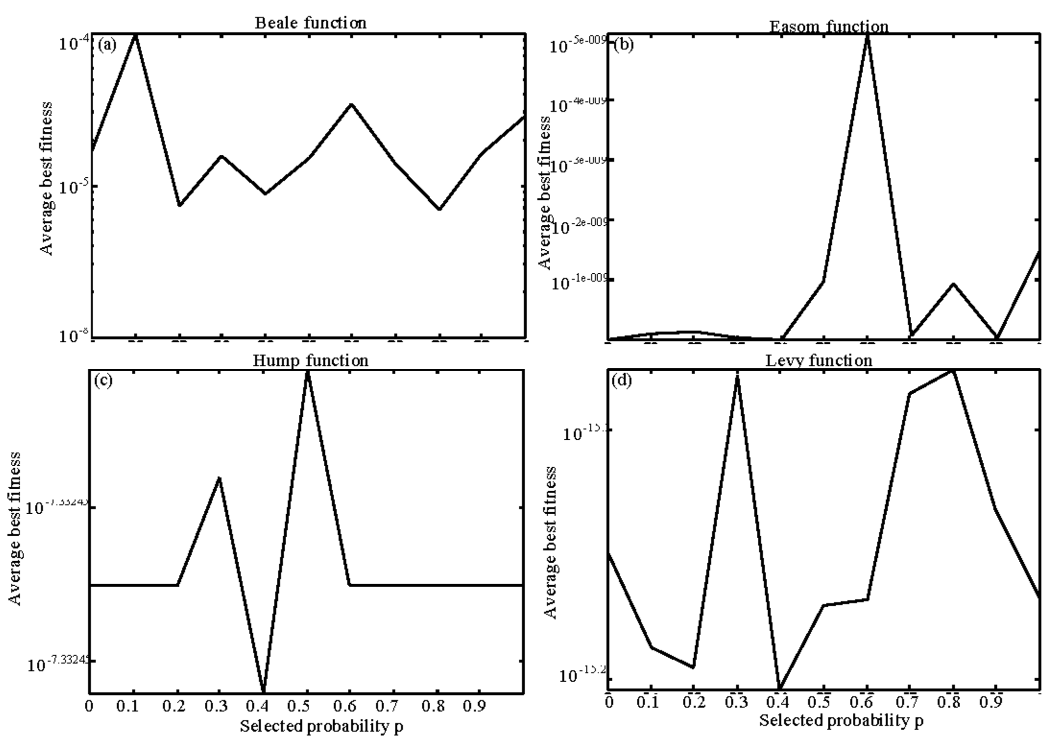

Fig. 1(a-d): Results on four test functions with different selective probability p, (a) Beale function, (b) Easom function, (c) Six Hump Camel Back function and (d) Levy function

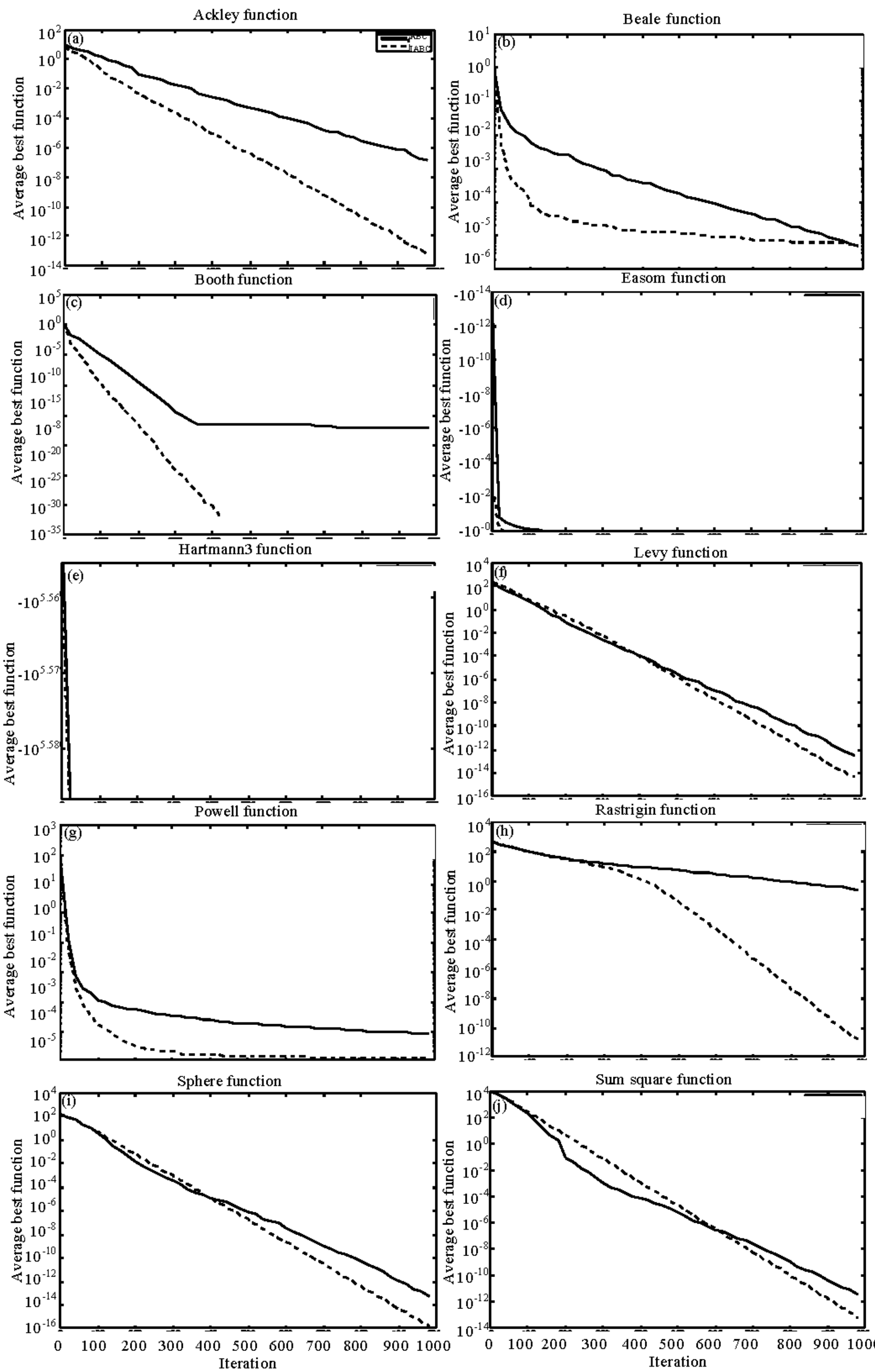

Fig. 2(a-j): Convergence processes of ABC and IABC on some test functions, (a) Ackley function, (b) Beale function, (c) Booth function, (d) Easom function, (e) Hump function, (f) Levy function, (g) Powell function, (h) Rastrigin function, (i) Sphere function and (j) Sum squares function

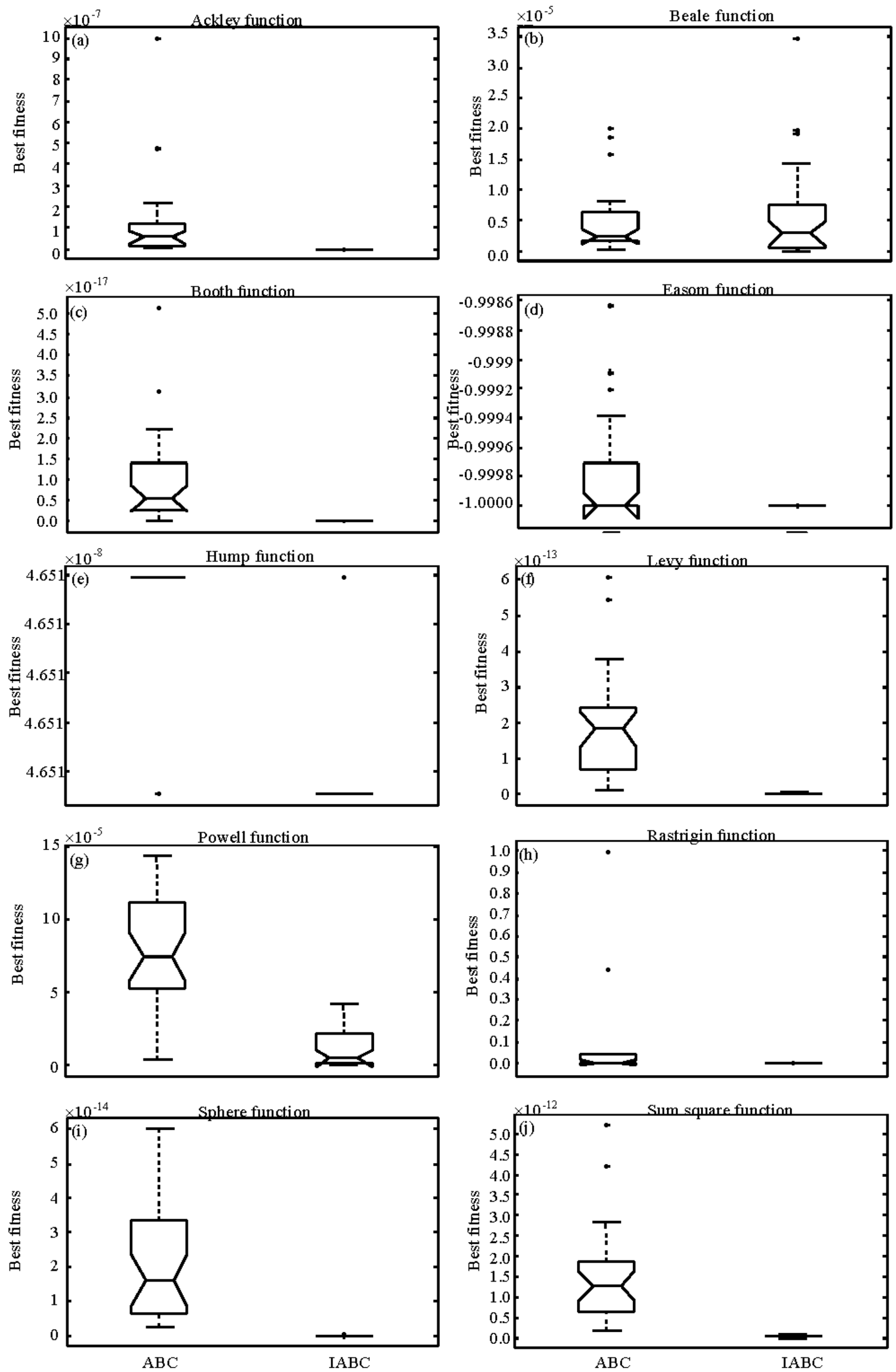

Fig. 3(a-j): Statistical values of the function values of ABC and IABC on some test functions, (a) Ackley function (b) Beale function, (c) Booth function, (d) Easom function, (e) Hump function, (f) Levy function, (g) Powell function, (h) Rastrigin function, (i) Sphere function and (j) Sum Squares function

Table 2: Best, worst, mean and standard deviation obtained by ABC and IABC

	ABC				IABC			
	Best	Mean	Worst	Std	Best	Mean	Worst	Std
f_1	3.93e-09	1.12e-07	1.00e-06	1.94e-07	3.55e-15	4.56e-14	5.61e-13	1.02e-13
f_2	7.08e-08	4.55e-06	2.01e-05	5.08e-06	7.16e-10	5.66e-06	3.48e-05	7.91e-06
f_3	3.78e-19	9.75e-18	5.13e-17	1.09e-17	0.00e+00	0.00e+00	0.00e+00	0.00e+00
f_4	-1	-0.99982	-0.99863	3.35e-04	-1	-1	-1	2.40e-09
f_5	4.65e-08	4.65e-08	4.65e-08	6.78e-17	4.65e-08	4.65e-08	4.65e-08	5.63e-17
f_6	1.45e-14	1.91e-13	6.06e-13	1.45e-13	5.23e-16	1.86e-15	4.69e-15	1.15e-15
f_7	3.67e-06	7.81e-05	1.43e-04	3.58e-05	4.17e-08	1.14e-05	4.22e-05	1.33e-05
f_8	5.14e-09	2.15e-01	9.95e-01	4.04e-01	4.55e-13	6.22e-12	8.23e-11	1.47e-11
f_9	2.76e-15	2.28e-14	6.03e-14	1.92e-14	2.78e-17	7.45e-17	1.86e-16	3.65e-17
f_{10}	1.56e-13	1.46e-12	5.23e-12	1.15e-12	8.09e-15	3.15e-14	6.56e-14	1.58e-14

algorithm on all test functions for standard deviation. All these results indicate that on the 10 test functions, the IABC algorithms obtain the better solutions than the original ABC algorithm.

In order to show the performance of the IABC algorithms more clearly, Fig. 2 shows the mean best function value of some functions. It is clear that for most functions the IABC algorithms have the better performance than the ABC algorithm. Particularly, the IABC algorithm performs the best, which can convergence to the optimum fast and stable.

Figure 3 shows the statistical results of the function values for 10 test functions. Here, box plots are used to illustrate the distribution of these samples obtained from 30 independent runs. The upper and lower ends of the box are the upper and lower quartiles. The line within the box represents the median and thin appendages summarize the spread a shape of the distribution. Symbol "+" indicate for outlier and the notches denote a robust estimation of the uncertainty about the medians for box-to-box comparison. From Fig. 3, we can see that IABC algorithms can obtain the better and more stable solutions than ABC algorithm does, which further verifies the discussion obtained in Table 2 and Fig. 2.

CONCLUSION

In this study, an improved artificial bee colony algorithm is developed for global optimization problems with opposition-based initialization method and new search mechanism. The experimental results tested on 10 benchmark functions show that IABC algorithms is competitive with ABC algorithm. The improvement can mainly be attributed to the following reasons. First, the new search mechanism can balance the exploration and exploitation abilities very well, which can both maintain the diversity and improve the convergent speed. Secondly, the initialization methods can affect the quality of the solutions and the convergence speed. Therefore, the IABC algorithms are accuracy and effective for global optimization problems.

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