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Undulating Swarm Intelligence Agents in Wave Increasing Evolved Bat Algorithm

Pei-Wei Tsai[1,2,*], Shunmiao Zhang[1], Jing Zhang[1],
Yuan Liu[1], Yao He[1], and Jeng-Shyang Pan[1,3]

[1]College of Information Science and Engineering
Fujian University of Technology
No.3, Xueyuan Road, Fuzhou City 350118, Fujian Province, China
pwtsai@fjut.edu.cn, zshunmiao@163.com, jing165455@126.com,
liuyuan@fjut.edu.cn, wonderkewen@163.com

[2]Key Laboratory for Automotive Electronics and Electric Drive of Fujian Province
Fujian University of Technology
No.3, Xueyuan Road, Fuzhou City 350118, Fujian Province, China

[3]Innovative Information Industry Research Center
Harbin Institute of Technology Shenzhen Graduate School
University Town, Shenzhen 518055, China
jspan@fjut.edu.cn

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Abstract. *Swarm intelligence algorithms utilize large amount of artificial agents to discover solutions in the solution space. Thus, the diversity in a group of artificial agents plays the major role that directly influences the searching result and the exploration capacity. However, an over-high exploration capacity is not helpful for pinpointing the near best solution in the searching domains. It implies that a good swarm intelligence algorithm for solving optimization problems should be capable to balance the abilities to explore and to exploit the solution space. Answering to the criteria of swarm intelligence algorithms, the evolved bat algorithm is improved by replacing the fixed maximum searching step size, which is determined by the media, with a continuously level increasing trigonometric function. The cosine signal and a level increasing direct current signal are employed in our design for improving the searching capacity of the evolved bat algorithm. In order to verify the performance and the searching accuracy of our proposed method, three test functions with known global optimum values are used in the experiments. In addition, every test function is tested with four different dimensional conditions, which include 10, 30, 50, and 100 dimensional test environments. The experimental results indicate that our proposed method improves the searching accuracy of the evolved bat algorithm about 30.171%, 50.737%, 47.454%, and 47.96%, respectively for different dimensional environments, in average.*

Keywords: Evolved Bat Algorithm, Swarm Intelligence, Periodic Signal, Optimization

1. **Introduction.** Evolved Bat Algorithm (EBA) [12] is one of the newly released algorithms for solving numerical optimization problems in Swarm Intelligence (SI) in recent years. Like other algorithms in SI, EBA takes the tinny intelligence existing in bat's natural instinct and uses its behavior of hunting for the prey to form the mathematical model. The experimental results indicate that EBA presents better accuracy and performance than the original Bat Algorithm (BA) [14]. However, EBA uses a fixed constant in the process of presenting the new solutions. The fixed constant sometimes forms a

bottleneck for the artificial agents to discover better solutions. In order to overcome this drawback, we use a mixture signal in the searching process to inject higher diversity to the artificial agents. Although the conventional EBA has the drawback mentioned above, it is still successfully used in finding feasible solutions for the LMI fuzzy Lyapunov non-linear time-delay system controller [8]. And BA is used in structural optimization [3], and multiobjective optimization [5].

Besides EBA, many algorithms in SI are also proposed one after another, and their applications include many fields in engineering. For example, Interactive Artificial Bee Colony (IABC) [11] is successfully used in the passive continuous authentication system [9]; Cat Swarm Optimization (CSO) [1, 2], is modified and applied in the scheduling problem [10], deploying Wireless Sensor Networks (WSN) [7, 4], designing linear antenna array synthesis [6], and constructing the medical image registration [13].

After revisiting the way EBA produces new solutions, we replace the fixed constant, which represents the medium, by a mixture signal composed of a periodical signal and a level-increasing Direct Current (DC) signal. The vibration is brought into the process to the artificial agents, and the diversity is also increased. In order to test the influence caused by our change, we use three test functions, of which the global optimum values are known, in the experiment. The experimental results indicate that our proposed method improves the searching accuracy of EBA about 44.081 percent in average. The rest of this paper is constructed as follows: in section 2, a brief review on EBA is given, the detail of our proposed method is revealed in section 3, the experiments and the experimental results are given in section 4, and the conclusions are made in the last section.

2. **Brief Review on Evolved Bat Algorithm.** Tsai et al. present the conventional EBA in 2012 by redesigning the operation of which BA finds new solutions. The control parameters are much simplified in EBA than in BA. The distance calculation in the active sonar system is employed to be part of the operation for moving the artificial agents. The movement of the artificial agents in EBA can be depicted by Eqs. (1)-(2):

$$D = 0.17 \cdot \Delta T \tag{1}$$

$$x_i^t = x_i^{t-1} + D \tag{2}$$

where ΔT is a random variable and $\Delta T \in [-1, 1]$, D denotes the distance between the current position to the prey, x_i^t represents a solution obtained by the i^{th} artificial agent at the t^{th} iteration.

Besides the regular movement, EBA also provides 50% chance for the artificial agents to further take the random walk process. The random walk process is operated by Eq. (3):

$$x_i^{t_R} = \beta \cdot (x_{best} - x_i^t) \tag{3}$$

where $x_i^{t_R}$ represents the artificial agent after the random walk operation, β denotes a random number and $\beta \in [0, 1]$, and x_{best} is the near best solution obtained in the past iterations.

The diagram of the conventional EBA is depicted in Fig. 1:

3. **Our Proposed Wave Increasing Evolved Bat Algorithm.** In EBA, the movement of the artificial agents requires a constant, which is defined based on the chosen medium, to bind a range of the movable distance. Although EBA allows users to set the range in different values according to their demand, the diversity implanted into the

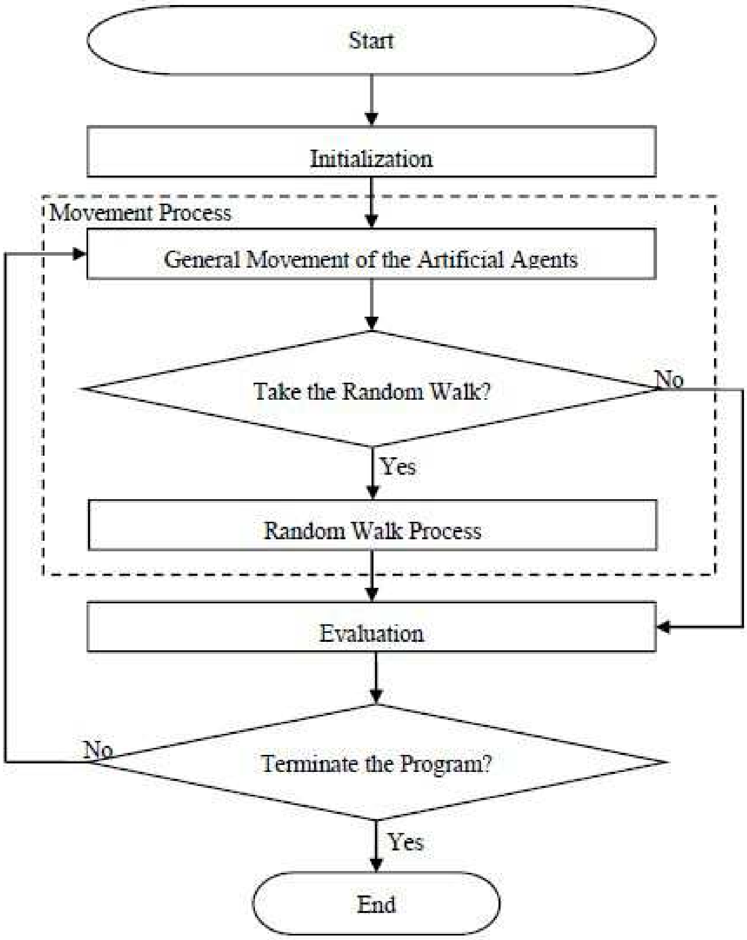

FIGURE 1. The diagram of EBA.

artificial agents is still not strong and powerful for exploring the solution space. To jump out of the bottleneck caused by the constant used in EBA, we use the most common detectable periodic signal in the natural environment, which is the cosine signal, and a linear increasing DC signal to mixture the compound signal. The reason of generating such a compound signal is that a simple cosine wave is not exactly fit for our goal. The other compound element, i.e., the level increasing DC signal provides an implemental gain of the energy for the artificial agents to move in the solution space. Let $Iter_{tot}$ denotes the total iteration number, our mixture signal can be compounded by Eq. (4):

$$Wave\,(t) = A \cdot \cos{(\omega t)} + \frac{t}{Iter_{tot}} \tag{4}$$

where $Wave\,(t)$ denotes the compounded mixture signal, A is the amplitude of the periodical signal, and ωt stands for the radius frequency. An example of the mixture signal is shown in Fig. 2.

As shown in Fig. 2, our proposed method utilize the mixture signal to increase the diversity of the searching range. The example given here uses $A = 2$ as the amplitude, and the length of a full cycle of the signal crosses 100 iterations.

To employ our proposed method in EBA, the process of the algorithm can be described as follows:

Step 1. Initialization: Randomly spread the artificial agents into the solution space.

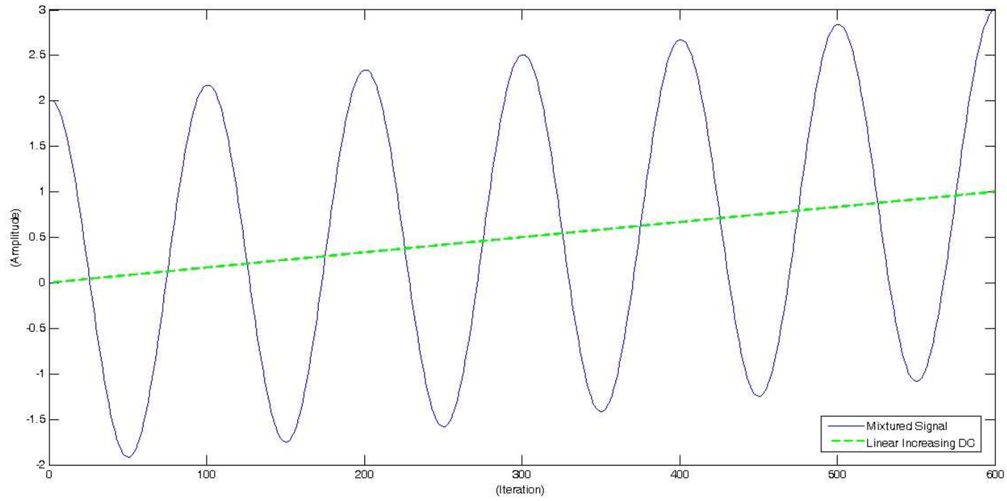

FIGURE 2. Sample of the mixture signal in our proposed method.

Step 2. Movement: Change the solutions of the artificial agent by Eqs. (4)-(5). Generate a random number to decide whether takes the random walk process. If the random walk process is taken into the operation, Eq. (3) is employed.

$$x_i^t = x_i^{t-1} + Wave\,(t) \cdot \Delta T \tag{5}$$

Step 3. Evaluation: Evaluate the fitness values of the artificial agents and update the near best solution found in the past iterations.

Step 4. Termination: If the termination condition is satisfied, terminate the program and output the near best solution; otherwise, go back to step 2 and repeat the process.

4. **Experiments and Experimental Results.** To find out whether our proposed method provides positive contribution to the searching capacity of EBA, three test functions with known global optimum are used in the experiment. The test functions are listed as follows:

$$f_1(X) = \sum_{i=1}^{n} x_i^2 - \sum_{i=1}^{n} cos(2\pi \cdot x_i) + 10 \cdot n \tag{6}$$

$$f_2(X) = 20 + e^1 - 20 \cdot e^{-0.2\sqrt{\sum_{i=1}^{n} \frac{x_i^2}{n}}} - e^{\sum_{i=1}^{n} \frac{cos(2\pi \cdot x_i)}{n}} \tag{7}$$

$$f_3(X) = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} cos(\frac{x_i}{\sqrt{i}}) + 1 \tag{8}$$

The goal of the optimizations of all test functions in the experiments is to find the minimum value of the benchmark function. Moreover, since EBA is one of the algorithm in evolutionary computing, the way it finds solutions can be said as a kind of guided random search. Thus, all experiments are taken with 25 complete runs for finding the average results. All test functions are tested with different dimensional conditions including 10, 30, 50, and 100 dimensions to proof the convergence exists in different dimensional conditions. In addition, the total iteration number is set to5000 for Eqs. (6)-(7) and 6000 for Eq.

(8), and the initial range of these functions are set to [-5.12, 5.12], [3, 13], and [-600, 600]. The parameter setting of the original EBA and our proposed WiEBA is given in Table 1.

Table 1. Parameters for EBA and WEBA

	EBA[11]	Our Proposed WiEBA
Fixed r	0.5	
ΔT	$[-1, 1]$	
A	NA	2

The experiments are taken with Matlab R2011b on a 64 bits Windows 8.1 operating system. Our experiments not only test the convergence speed, but also test for the accuracy on finding the near best solutions. To survey the accuracy, the final fitness values of all test functions are listed in Table 2 to Table 5, respectively, for compare.

Table 2. The Average Results over 25 Runs in 10 Dimensional Environment

	EBA[11]	Our Proposed WiEBA
$f_1(X)$	13.6922	14.7971
$f_2(X)$	14.3482	1.3547
$f_3(X)$	6.2623	5.7598

Table 3. The Average Results over 25 Runs in 30 Dimensional Environment

	EBA[11]	Our Proposed WiEBA
$f_1(X)$	88.3977	66.8171
$f_2(X)$	15.4204	11.1106
$f_3(X)$	13.3793	0.0203

Table 4. The Average Results over 25 Runs in 50 Dimensional Environment

	EBA[11]	Our Proposed WiEBA
$f_1(X)$	184.2451	125.8506
$f_2(X)$	15.7695	14.0819
$f_3(X)$	65.965	0.0218

As given in Table 2 to Table 5, all results obtained by our porposed WiEBA are more accurate in finding the near best solutions except the result from Eq. (7) in the 10 dimensional condition. As the known truth, the searching results are obtained base on the random numbers generated in the searching process in swarm intelligence algorithms. This unsatisfactory result is considered appeared by chance because it is only one special case exists in 12 different experiments.

Fig. 3 to Fig. 5 show the convergence of the fitness values in all test functions with different dimensional environment conditions. It is obvious that the convergence of WiEBA presents faster convergence and higher accuracy in finding the near best solutions.

The graphical results show that both EBA and WiEBA are capable to convergence to the near best solutions. Some graphics are presented with log scales on the axes to lay stress on the changes of the fitness values.

Table 5. The Average Results over 25 Runs in 100 Dimensional Environment

	EBA[11]	Our Proposed WiEBA
$f_1(X)$	495.1367	303.4329
$f_2(X)$	16.2981	15.4474
$f_3(X)$	270.2125	0.152

5. **Conclusions.** In this paper, EBA is improved by replacing the fixed constant used in the movement of the artificial agents by a continuously level-increased mixture signal. The signal is compounded of a periodical trigonometric signal and a linear raising DC signal. The experimental results indicate that our proposed WiEBA improves the searching accuracy of EBA about 30.171%, 50.737%, 47.454%, and 47.96% in average under 10, 30, 50, and 100 dimensional conditions. The average improvement in all conditions and test functions is significant at 44.081%.

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REFERENCES

[1] S.-C. Chu, and P.-W. Tsai, Computational Intelligence Based on the Behavior of Cats, *International Journal of Innovative Computing, Information and Control*, vol. 3, no. 1, pp. 163-173, 2007.

[2] S.-C. Chu, P.-W. Tsai, and J.-S. Pan, Cat Swarm Optimization, *Lecture Notes in Computer Science*, vol. 4099, pp. 854-858, 2006.

[3] O. Hasanebi, T. Teke, and O. Pekcan, A bat-inspired algorithm for structural optimization, *Computers and Structures*, vol. 128, pp. 77-90, 2013.

[4] L. Kong, J.-S. Pan, P.-W. Tsai, S. Vaclav, and J.-H. Ho, A Balanced Power Consumption Algorithm Based on Enhanced Parallel Cat Swarm Optimization for Wireless Sensor Network, *International Journal of Distributed Sensor Networks*, vol. 2015, pp. 1-10, 2015.

[5] T. Niknam, R. A zizipanah-Abarghooee, M. Zare, and B.Bahmani-Firouzi, Reserve Constrained Dynamic Environmental/Economic Dispatch: A New Multi-objective Self-Adaptive Learning Bat Algorithm, *IEEE Systems Journal*, vol. 7, no. 4, pp. 763-776, 2013.

[6] L. Pappula and D. Ghosh, Linear antenna array synthesis using cat swarm optimization, *International Journal of Electronics and Communications (AE)*, vol. 68, pp. 540-549, 2014.

[7] S. Temel, N. Unaldi, and O. Kaynak, On Deployment of Wireless Sensors on 3-D Terrains to Maximize Sensing Coverage by Utilizing Cat Swarm Optimization with Wavelet Transform, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 44, no. 1, pp. 111-120, 2014.

[8] P.-W. Tsai and C.-W. Chen, A Novel Criterion for Nonlinear Time-Delay Systems Using LMI Fuzzy Lyapunov Method, *Applied Soft Computing*, vol. 25, pp. 461-472, 2014.

[9] P.-W. Tsai, M. K. Khan, J.-S. Pan, and B.-Y. Liao, Interactive Artificial Bee Colony Supported Passive Continuous Authentication System, *IEEE Systems Journal*, vol. PP, pp. 1-11, 2012.

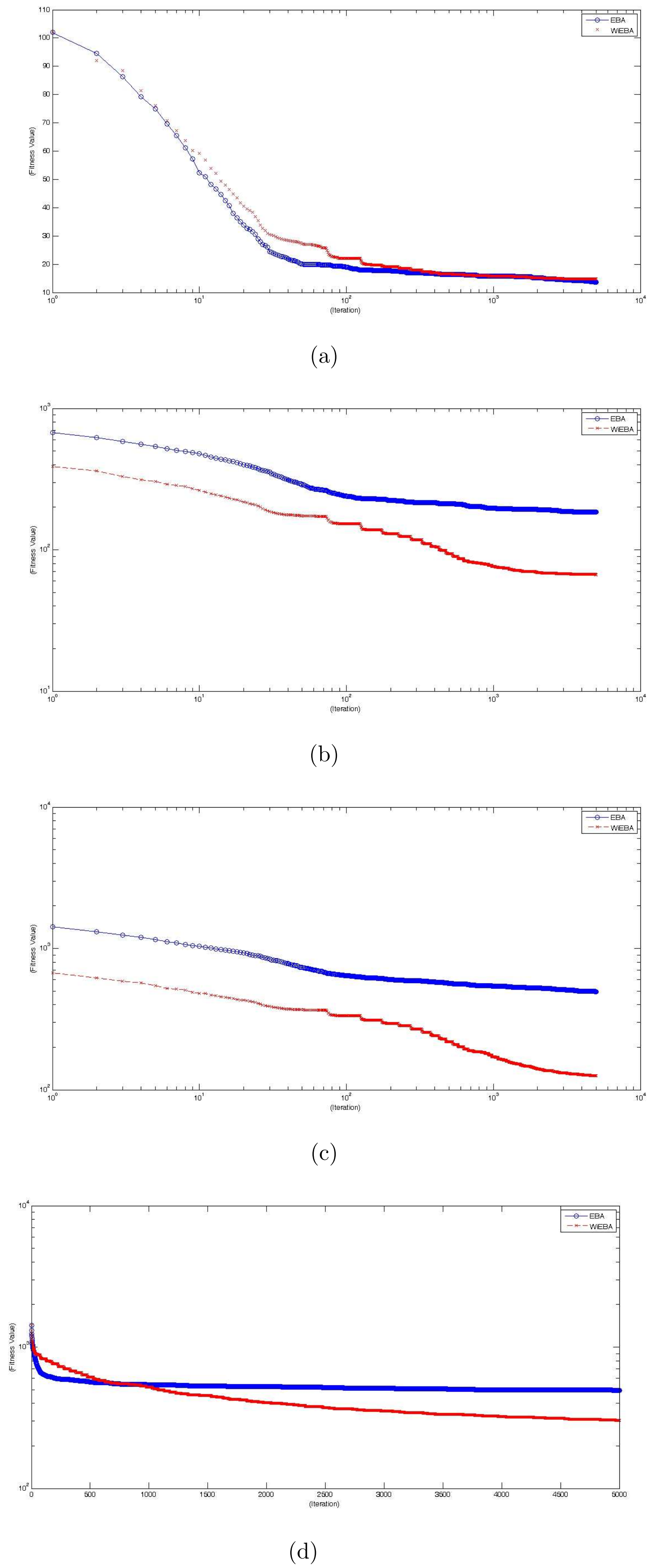
[10] P.-W. Tsai, J.-S. Pan, S.-M. Chen, and B.-Y. Liao, Enhanced Parallel Cat Swarm Optimization Based on the Taguchi Method, *Expert Systems with Applications*, vol. 39, no. 7, pp. 6309-6319, 2012.

[11] P.-W., Tsai, J.-S. Pan, B.-Y. Liao, and S.-C. Chu, Ehanced Artificial Bee Colony Optimization, *International Journal of Innovative Computing, Information and Control*, vol. 5, no.12(B), pp. 5081-5092, 2009.

[12] P.-W. Tsai, J.-S. Pan, B.-Y. Liao, M.-J. Tsai, and I. Vaci, Bat Algorithm Inspired Algorithm for Solving Numerical Optimization Problems, *Applied Mechanics and Materials*, vol. 148-149, pp. 134-137, 2012.

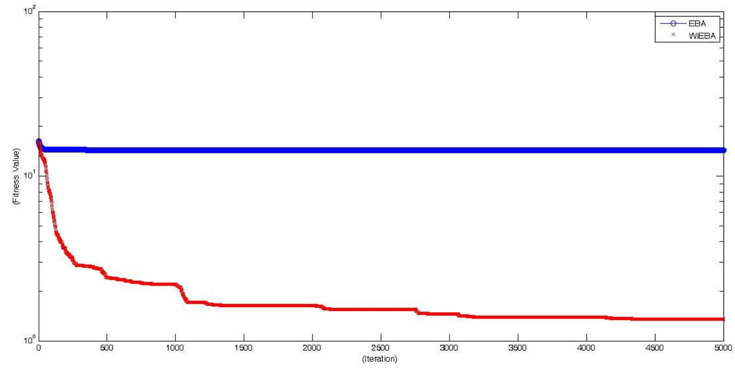
[13] F. Yang, M. Ding, X. Zhang, W. Hou, and C. Zhong, Non-rigid multi-modal medical image registration by combining L-BFGS-B with cat swarm optimization, *Information Sciences*, *in Press*, 2015.

[14] X.-S. Yang, A New Metaheuristic Bat-Inspired Algorithm. In: Nature Inspired Cooperative Strategies for Optimization (NICSO 2010), Studies in Computational In-telligence 284, J. R. Gonzlez, D. A. Pelta, C. Cruz, G. Terrazas, and N. Krasnogor (eds.), Springer-Verlag/Berlin Heidelberg, pp. 65-74, 2010.

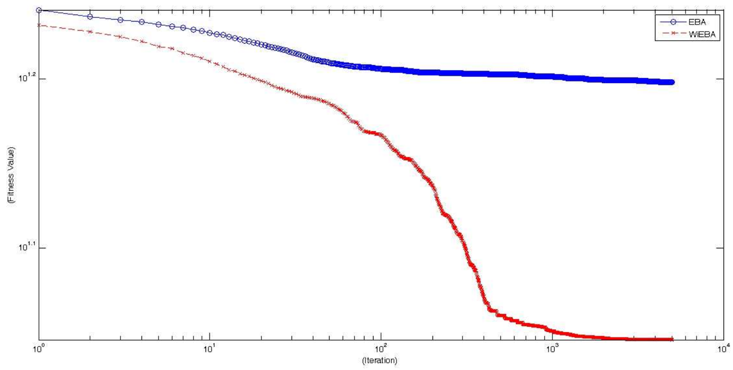


(a) (b) (c) (d)

FIGURE 3. The fitness values of test function $f_1(X)$: (a) 10-D space, (b) 30-D space, (c) 50-D space, and (d) 100-D space.



(a)



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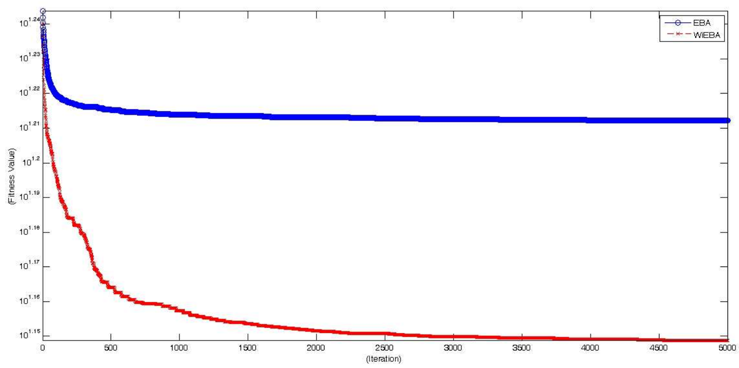

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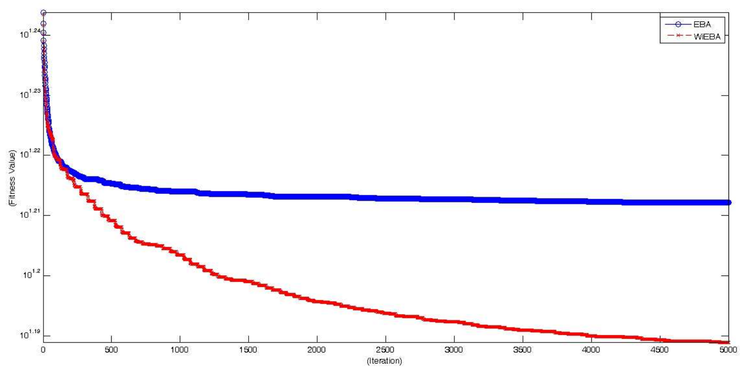
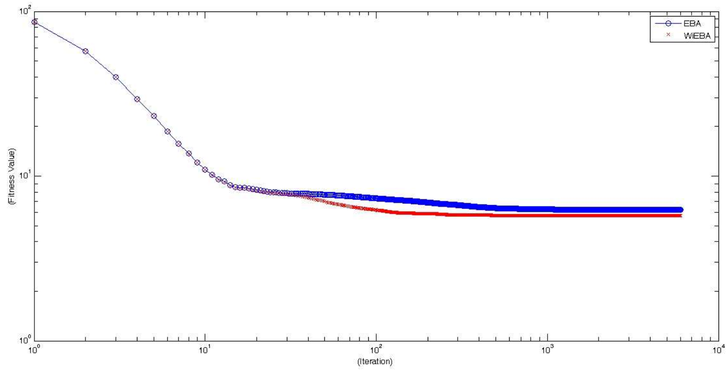


(d)

FIGURE 4. The fitness values of test function $f_2(X)$: (a) 10-D space, (b) 30-D space, (c) 50-D space, and (d) 100-D space.



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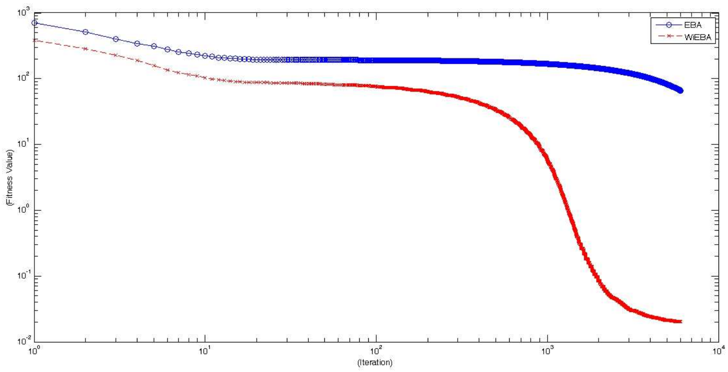

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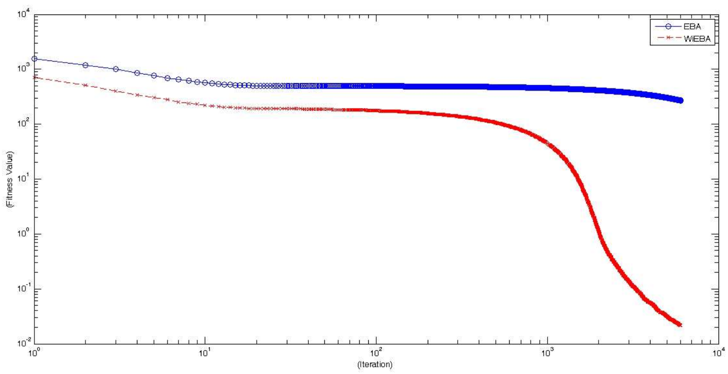

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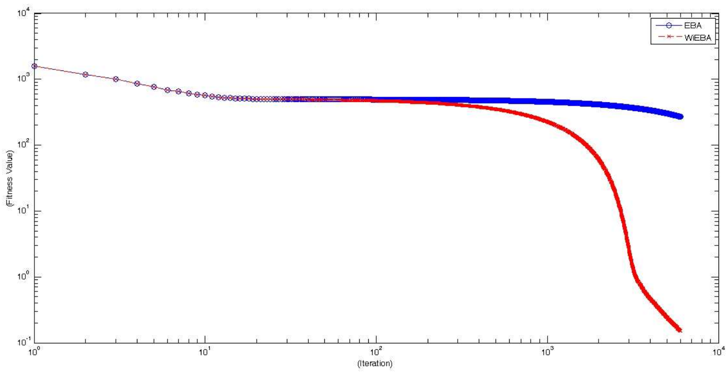

(d)

FIGURE 5. The fitness values of test function $f_3(X)$: (a) 10-D space, (b) 30-D space, (c) 50-D space, and (d) 100-D space.