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Improving Swarm Intelligence Accuracy with Cosine Functions for Evolved Bat Algorithm

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Abstract. *The diversity created during the searching process in swarm intelligence algorithms plays an important part that affects the exploration ability. The searching result can be further improved if the algorithm gives consideration to both the exploitation and the exploration. In this paper, the evolved bat algorithm is improved by replacing the fixed value, which is determined by the media, with a cosine function. The familiar trigonometric signal exists in the natural environment is the sine/cosine signal. We take the cosine signal in our design for improving the searching capacity of the evolved bat algorithm. To verify the performance and the searching accuracy of our proposed strategy, three test functions with known global optimum values are used in the experiments. Moreover, every test function is tested with four different dimensional criteria, which include 10, 30, 50, and 100 dimensional test environments. The experimental results indicate that our proposed strategy improves the searching accuracy of the evolved bat algorithm about 28.098%, 48.779%, 45.945%, and 48.81%, respectively for different dimensional environments, in average.*

Keywords: Evolved Bat Algorithm, Swarm Intelligence, Periodic Signal, Cosine Function, Optimization.

1. **Introduction.** Swarm Intelligence (SI) is a solid branch in evolutionary computing. Most algorithms in SI take tinny intelligence observed from creatures in Mother Nature as the guidance for dragging the artificial agents to find new solutions in optimization. Many algorithms in SI are proposed one after another in recent years. For instant, Cat Swarm Optimization (CSO) [1, 2], utilizes the seeking mode to simulate the cat is observing

the environment and the tracing mode to imitate the coursing behavior. In addition, many improved version of CSO has been presented in recent years and its applications are also proposed one after another. For example, Temel et al. utilize CSO with wavelet transform to maximize the sensing coverage in Wireless Sensor Network (WSN) [11], Pappula and Ghosh employ CSO in linear antenna array synthesis [10], and Yang et al. use CSO with the limited memory Broyden-Fletcher-Goldfarb-Shanno with boundaries (L-BFGS-B) method to calibrate the medical image registration [13]. On the other hand, Evolved Bat Algorithm (EBA) [12] is proposed in 2012 for solving numerical optimization problems by simulating the behavior of bats searching for prey in the space. EBA is an inspired algorithm from the original Bat Algorithm (BA) [14]. The related applications of BA include structural optimization [3]; Niknam et al. utilize BA in finding the linear supply function equilibrium of GENCOs in the competitive electricity market [9]; and BA is also used in solving multiobjective optimization problems in reserve constrained dynamic environmental economic dispatch [8].

In this paper, we focus on further improving the searching capacity of EBA by leading the periodical signal in the searching operation. The periodical signal brings in the vibration to the artificial agents and provides larger diversity of the individuals. To test the influence of leading the periodic signal in the searching process, three test functions are employed in the experiments. The experimental results indicate that our proposed strategy improves the searching accuracy of the evolved bat algorithm about 44.081% in average of all experiments with different dimensional environments. The rest of the paper is constructed as follows: a brief review of EBA is given in section 2, our proposed strategy is described in detail in section 3, the experiments and the experimental results are given in section 4, and the conclusions are made at last.

2. **Review on Evolved Bat Algorithm.** In 2012, Tsai et al. present EBA by redesigning the movement operation of the original BA and simplifying the control parameters required by the algorithm. The distance calculation based on the active sonar system is taken into account in the artificial agents movement. The key element of the movement of the artificial agent in EBA is processed by Eqs. (1)-(2):

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

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

where D denotes the distance between the current position to the prey, ΔT is a random variable and $\Delta T \in [-1, 1]$, x_i^t represents a solution obtained by the i^{th} artificial agent at the t^{th} iteration. In addition, every artificial agent has half chance to be further processed by the random walk operation by Eq. (3):

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

where $x_i^{t_R}$ indicates the artificial agent after the random walk operation, β is a random number in the range of [0, 1], and x_{best} stands for the near best solution obtained in the past iterations.

The process of EBA is briefly reviewed as follows:

Step 1. Initialization: Spread the artificial agents into the solution space.

Step 2. Movement: Change the solutions of the artificial agent by Eqs. (1)-(2). 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.

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.

3. **Our Proposed Waving Evolved Bat Algorithm.** When presenting EAB, Tsai et al. choose the air to be the medium for carrying the sound wave. Based on the known truth, the sound speed spreads in the air is 340 meters per second. In addition, the sound wave actually travels twice far from the wave source to the prey and the traveling direction is taken in the consideration. Hence, the travel distance in EBA is a fixed range in $[-0.17, 0.17]$. Although the users may set the range in different values by their own design, the diversity pumped into the artificial agents is still not strong and powerful for exploring the solution space. To overcome this drawback, we employ the periodic signal to replace the fixed limit. The most common periodic signal, which can be detected in the nature environment is the cosine signal. Hence, we inject the cosine signal into the movement of the algorithm to provide larger diversities. In our proposed strategy, the movement of the artificial agent is processed by Eqs. (4)-(5):

$$Wave = A \cdot \cos(\omega t) \tag{4}$$

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

where $Wave$ denotes the periodical signal employed in the operation, and A is the amplitude of the signal.

In our design, a full cycle of the injected periodical signal is defined by Eq. (6):

$$T = \frac{1}{t_i} \tag{6}$$

where T stands for the cycle and t_i indicates a set of number of iterations.

We call our proposed method Waving Evolved Bat Algorithm (WEBA) because the proposed strategy varies the travel distance limit of artificial agents base on the cosine function. An example of the injected periodical signal is shown in Fig. 1.

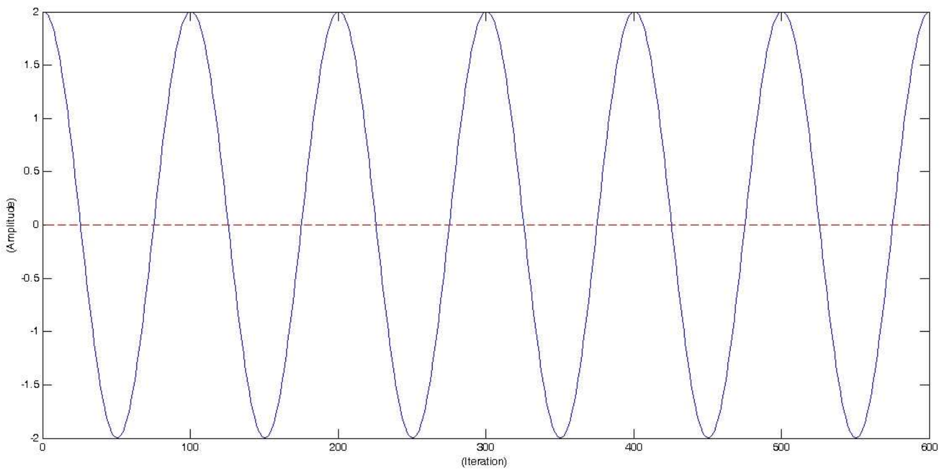

FIGURE 1. Sample of the injected cosine signal for our proposed WEBA

As shown in Fig. 1, our proposed strategy utilize the cosine 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.

4. **Experiments and Experimental Results.** To test the impact to the searching capacity brought by our proposed strategy, three test functions with known global optimum are used in the experiments. The test functions are listed in Eqs. (7)-(9):

$$f_1(X) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} cos(\frac{x_i}{\sqrt{i}}) + 1 \tag{7}$$

$$f_2(X) = 20 + e^1 - 20 \cdot e^{-0.2\sqrt{\sum_{i=1}^{n}\frac{x_i^2}{n}}} - e^{\sum_{i=1}^{n}\frac{cos(2\pi \cdot x_i)}{n}} \tag{8}$$

$$f_3(X) = \sum_{i=1}^{n} x_i^2 - \sum_{i=1}^{n} cos(2\pi \cdot x_i) + 10 \cdot n \tag{9}$$

As the same as most engineering applications, the goal of the optimizations of all test functions is to find the minimum value of the benchmark. The dimension of all test functions is set to 10, 30, 50, and 100, respectively; all experiments are repeated for 25 runs for finding the average results. The total iteration number is set to 6000 for Eq. (7) and 5000 for Eqs. (8)-(9), and the initial range of these functions are set to $[-600, 600]$, $[3, 13]$, and $[-5.12, 5.12]$. The parameter setting of the original EBA and WEBA is given in Table 1.

Table 1. Parameters for EBA and WEBA

	EBA[12]	Our Proposed WEBA
Fixed r	0.5	
ΔT	$[-1, 1]$	
A	NA	2

The final fitness values of all test functions with different dimensional conditions are listed in Table 2 to Table 5, respectively.

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

	EBA[12]	Our Proposed WEBA
$f_1(X)$	6.2623	5.6148
$f_2(X)$	14.3482	1.7646
$f_3(X)$	13.6922	15.5745

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

	EBA[12]	Our Proposed WEBA
$f_1(X)$	13.3793	0.0253
$f_2(X)$	15.4204	11.9107
$f_3(X)$	88.3977	67.3897

As given in Table 2 to Table 5, all results obtained by our porposed WEBA are more accurate in finding the near best solutions except the result from Eq. (9) in the 10 dimensional environment. As the known truth, the searching results are obtained base on the random numbers generated in the searching process in swarm intelligence algorithms.

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

	EBA[12]	Our Proposed WEBA
$f_1(X)$	65.965	0.0196
$f_2(X)$	15.7695	14.602
$f_3(X)$	184.2451	128.1194

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

	EBA[12]	Our Proposed WEBA
$f_1(X)$	270.2125	0.155
$f_2(X)$	16.2981	15.4209
$f_3(X)$	495.1367	291.6105

This unsatisfactory result is considered appeared by chance because it is only one special case exists in 12 different experiments.

Fig. 2 to Fig. 4 show the convergence of the fitness values in all test functions with different dimensional environment conditions. It is obvious that the convergence of WEBA presents faster convergence and higher accuracy in finding the near best solutions.

The graphical results show that both EBA and WEBA 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. The difference between the conventional EBA and our porposed WEBA is only on the fixed boundary parameter versus the injected cosine signal. Moreover, swarm intelligence algorithms basically search for better results by a controllable random process. The larger the diversity of the artificial agent is, the bigger the chance to find better result is. Hence, we can conclude that the improved searching results are caused by the joint of the periodical signal.

5. **Conclusions.** In this paper, we propose a strategy, which injects a cosine signal into the process of EBA. We use the cosign wave, which is the most common periodical signal can be detected in the nature environment, to reformat the equations employed in the movement process in EBA. It results in the increasing of the diversity of artificial agents when searching for new solutions. To test the usability of this strategy, three fitness functions with known global optimal in 4 different dimensional conditions are used in the experiments. The accuracy of finding the near best solution of our proposed strategy is compared with the conventional EBA. The experimental results indicates that our proposed WEBA significantly improves the searching accuracy about 42.908% in average. In the future work, we will focus on improving the searching efficiency of the swarm intelligence algorithm. Furthermore, some industrial applications such as combining EBA algorithm with the intelligent information hiding algorithms [15, 7, 4, 5, 6] may be taken into considered for combining with the swarm intelligence algorithms.

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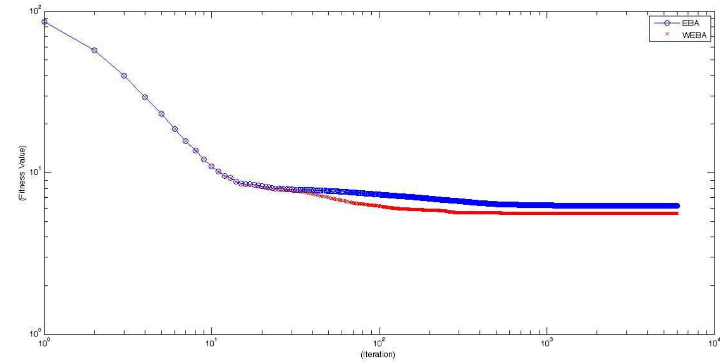

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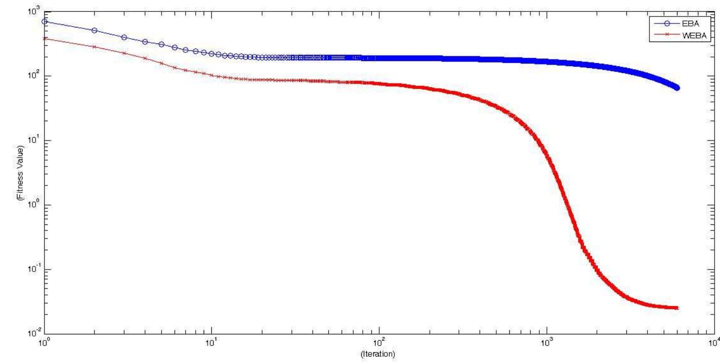

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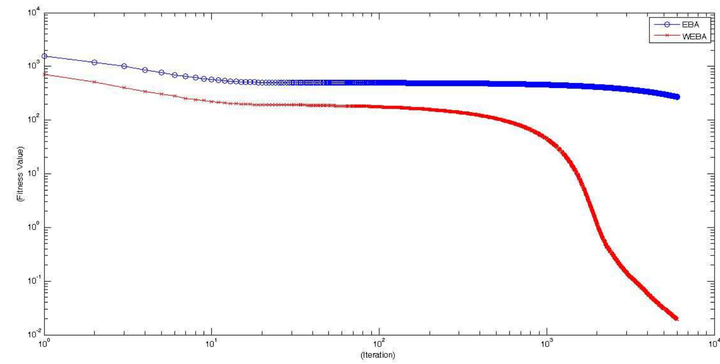

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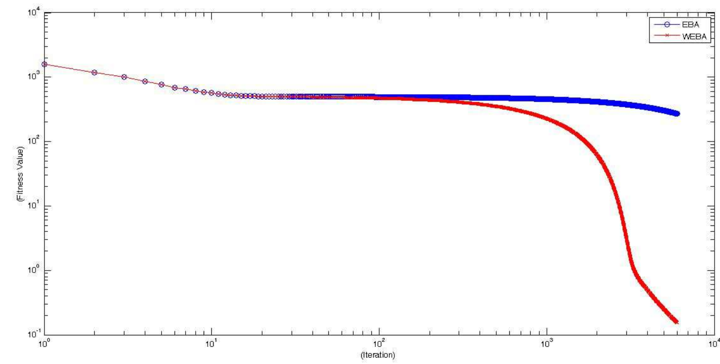
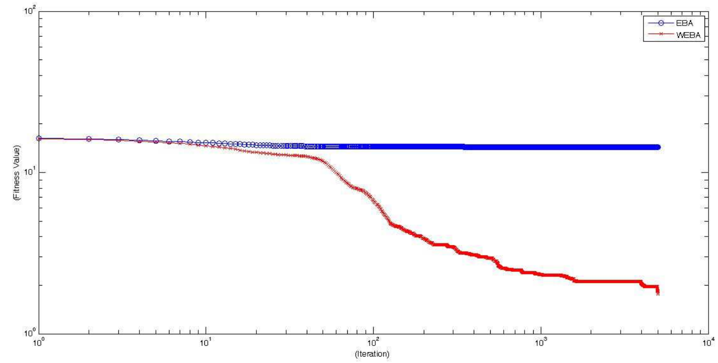


(d)

FIGURE 2. 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.



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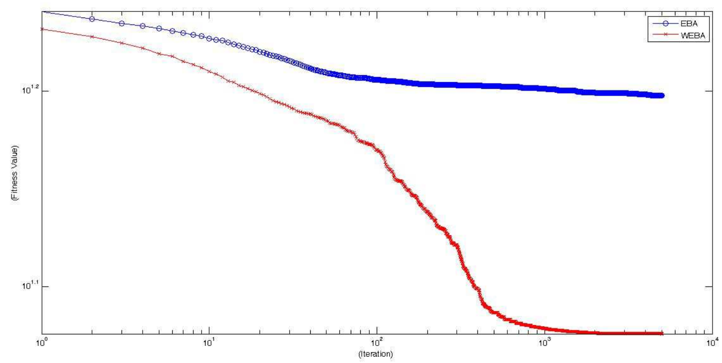

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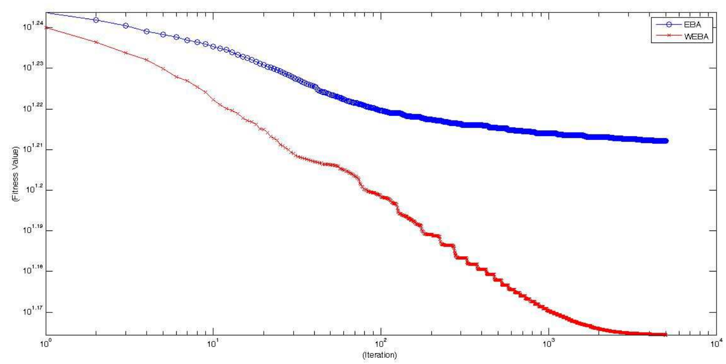

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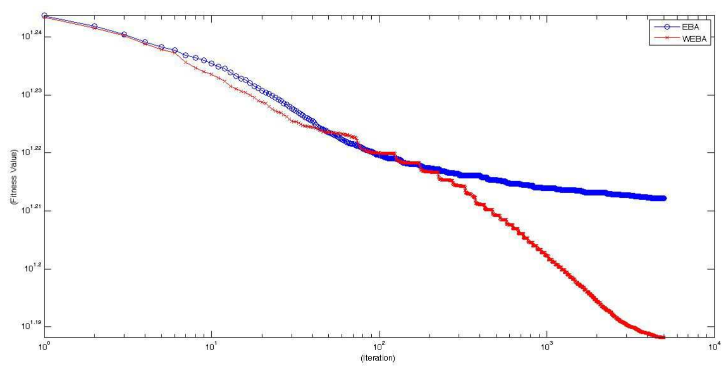

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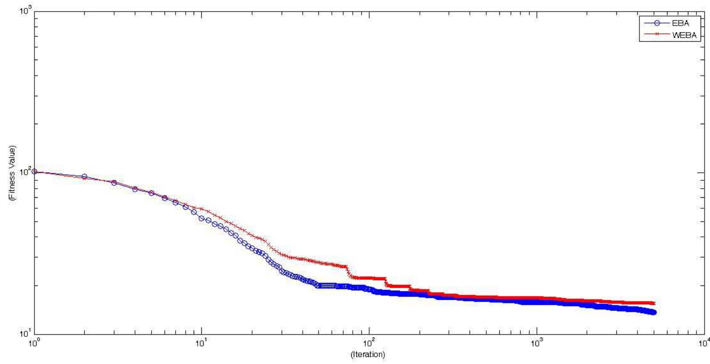
FIGURE 3. The fitness values of test function $f_2(X)$: (a) 10-D space, (b) 30-D space, (c) 50-D space, and (d) 100-D space.



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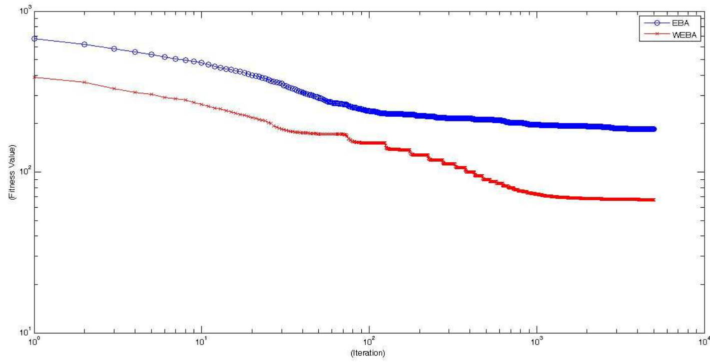

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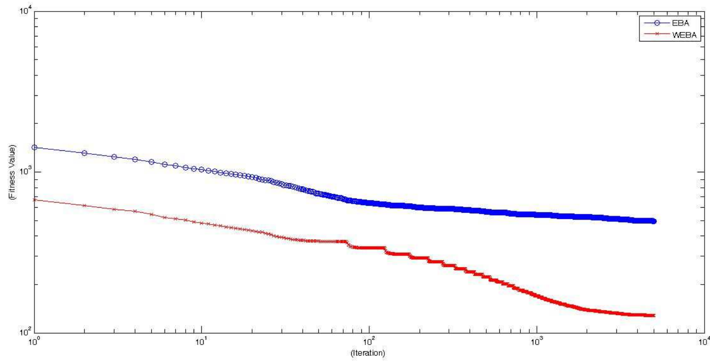

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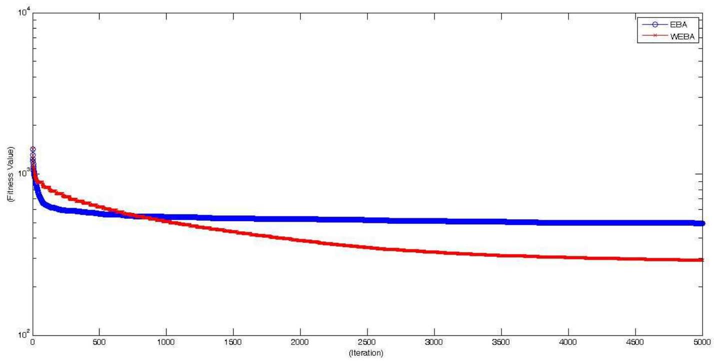

(d)

FIGURE 4. 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.