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Echolocation Guided Evolved Bat Algorithm

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Abstract. *The artificial agents in Evolved Bat Algorithm(EBA) are lacked of echoic guidance feature, so the artificial agents sometimes would cause the slow convergence to the global or near best optimum. To overcome the drawbacks, an improved bio-inspired swarm intelligence algorithm, entitled Echolocation Guided Evolved Bat Algorithm (EGEBA), based on the frame of EBA is proposed in this paper. In EGEBA, our design guides the artificial agents to the near best solution via the directional information calculated by echolocation. 8 well-known fitness functions are employed to validate the performance of EGEBA, and the experimental results reveal that the solutions obtained by our proposed EGEBA are superior to the conventional EBA in terms of the solution quality, the robustness, and the convergence.*
Keywords: Evolved Bat Algorithm, Echolocation guided, Swarm Intelligence, Artificial Agent, Optimization.

1. **Introduction.** Optimization problems are very common to be find in many different applications of engineering and the industrial designs[1,2], such as UCAV path planning[3], welded beam[4], WSN deployment[5], etc. Since most real-world and complex optimizations are often nonlinear, they always employ metaheuristic algorithms to tackle. In recent years, many bio-inspired algorithms are proposed one after another to solve these optimization problems, e.g., Ant Colony Optimization(ACO)[6], Particle Swarm Optimization(PSO)[7,8,9], Artificial Bee Colony(ABC)[10,11], Biogeography-based Optimization(BBO)[12,13], Differential Evolution(DE)[14,15,16] and Bat Algorithm(BA)[17]. Such algorithms attempt to mimic natural phenomena and utilize intensification and diversification to generate better solutions[17]. The computational efficiency of these algorithms is increased by using iterations and stochasticity, such as BA, the performance and effectiveness of it is superior than FA, GSA, HS and PSO[18 ,19].

In 2010, Yang proposed a bio-inspired algorithm developed by the echolocation characteristics of bat's behaviors entitled Bat Algorithm [20]. BA is efficient to implement for the three key features: frequency tuning, automatic zooming and parameter control[20]. BA is simple and flexible on lower-dimensional optimizations, but it may become problematic for higher-dimensional optimizations[21]. Hence, Tsai et al. proposed EBA [22] to improve the performance and accuracy of the conventional BA. The conventional movement process in EBA is updated by the distance that sounds travel forward and backward in the air during the time interval, and the orientation of movement is stochastic. Obviously, it is markedly different from the real-world movement of bats because it lacks of the most essential echoic guidance feature of bats. Therefore, we introduce the echoic guidance into EBA to avoid the blind search. As the result, an Echolocation Guided Evolved Bat Algorithm (EGEBA) is proposed. The EGEBA has been tested on a standard set of benchmark functions gathered from the literatures. The experimental results indicate that the performance, the accuracy and the convergence of EGEBA is significantly superior to the conventional EBA.

The remainder of the paper is organized as follows: the conventional EBA and our proposed EGEBA are described in section 2 and section 3, respectively. The detail of the simulations of both algorithms are presented in section 4. Finally, the conclusions are given in section 5 with suggestions for the future works.

2. **Literatures Review.** Bats emit a high sound frequency and listen for the echo that bounces back from the surrounding objects. Echolocation is one kind of sonar, which is utilized to pinpoint prey and avoid obstacles[17]. Yang developed bat algorithm inspired by the echolocation feature of bats. Tsai et al. proposed EBA based on the structure of BA[24]. The new solution is generated by Eq.(1).

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

where D is the displacement during the time interval and it can be expressed as follow:

$$D = \frac{V \cdot \Delta T}{2} = 0.17 \cdot \Delta T(km/s) \tag{2}$$

where V is the sound speed and $\Delta T \in [-1, 1]$ is the time difference. The random walk process is designed after the normal movement. The process is executed stochastic, which is defined by Eq.(3)

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

where $x_i^{t_R}$ is the new location, β is a random number in the range of [0, 1], and x_{best} is the near best solution.

Bats use echoes to sense the distance and orientation of the target. But the distance calculated by echo is directly updated instead of guiding in the standard movement of EBA given by Eq.(1)-(2), and the model of EBA doesn't have the parameter of orientation. Just uses a random number in the range of [-1,1] to denote ΔT[24]. The most important echolocation characteristic of bats is ignored in EBA. Though the EBA is more accurate than BA, this undirected search has caused the slow convergence of the algorithm to the optimum or near optimum.

3. **Our approach: EGEBA.** It is generally known, echolocation is a highlighted part of bats behavior, so the echo guidance is introduced to our approach, and movement processes of EGEBA can be constituted by 3 steps: echo guide, standard movement and random walk process.

The first step is echo guide procedure to calculate the oriented parameter(Λ) of each dimension for every particle. At the first beginning, the new location to which the sound speeds spreads in the air after ΔT is operated by Eq.(4).

$$x_{si}^t = x_{si}^{t-1} + v \cdot \Delta T \tag{4}$$

where v is the sound speed,$\Delta T \in [0,1]$ is the time difference. Then, the oriented parameter(Λ) is determined by the comparison of fitness values corresponding to $x_{si}^t and x_{si}^{(t-1)}$, respectively. If the fitness value of x_{si}^t is better than the value of $x_{si}^{(t-1)}$, the parameter(Λ) is set to 1, otherwise Λ is set to -1. If the fitness value of x_{si}^t is equal to the value of $x_{si}^{(t-1)}$, Λ is set to 0. The second step is standard movement generating the new solutions by performing the following equation:

$$x_{id}^t = x_{id}^{t-1} + \Lambda \cdot \alpha \cdot (P_{id} - x_i^{t-1}) + \Lambda \cdot \beta \cdot (P_{ed} - x_i^{t-1}) \tag{5}$$

where Λ is the oriented parameter(-1,1,0), α and β are the random numbers generated from a uniform distribution in the region of [0,1], P_{id} is the best historical position of particle i, the P_{ed} is the best historical position of entire swarm. The last step is a random walk process, which is generally known as the optional process. It provides an opportunity for particle i to further move one more step to cope with the problem of local optimum[25]. The new solution is given by Eq.(6).

$$x_{id}^{t_R} = \zeta \cdot (P_{ed} - x_i^t) \tag{6}$$

where ζ is a random number of a uniform distribution in [0,1].

4. **Numerical Simulations and Experimental Results.** The experiments are implemented on Lenovo notebook with Intel(R) Core(TM) i5-3210M @2.50GHz, 10.00 GB RAM, 64 bits OS and MATLAB 2010a running under windows 7. In the experiments, the conventional EBA is employed as the baseline to compare with our proposed EGEBA.

4.1. **The parameters and Benchmark functions.** The parameters of EBA and EGEBA are equal to each other for the sake of making a clear and consistent comparison. In order to test the influence of dimension for the result, four different sets of dimensions are attended to, i.e. D=10, D=20, D=30 and D=50. Each experiment is repeated 25 runs with different random seeds, and the population size is set to 20.

The 8 well-known benchmark functions taken from the literature are utilized. The expression of each function, along with initial range, dimensions and number of iteration are presented in Table 1.

4.2. **The results.** The results summarized in Table 2. are measured according to the best, worst and mean in these runs.

Table 2 represents the results of EGEBA and EBA executing the testing suite of eight functions with dimensions D=10, 20,30 and 50, respectively. The results show that EGEBA significantly exalted the effectiveness, accuracy and convergence of EBA, according to almost all simulations except one case function $3(f_3)$ with dimension D=50. The result of EGEBA and EBA by function 7 is same, but the iteration number of EGEBA is smaller than EBA just as Fig.7.

In order to precise observe how the performances of EGEBA and EBA, modified with the dimensions of functions, the mean value of function $1(f_1)$ to function $8(f_8)$ with dimensions D=10, 20, 30 and 50 are drawn in Figs.1-8.

TABLE 1. Benchmark functions used in the experiments

No.	Formulation	Range	Dimensions	Iteration	f_{min}
f_1	$f(x) = a_0 + \sum_{i=1}^{d}(\sum_{k=0}^{kmax}(a^k \cos(2\pi b^k(x_i + 0.5)))) - D\sum_{k=0}^{kmax}(a^k \cos(2\pi b^k * (0.5))$ $(a = 0.5, b = 3, k_{max} = 20)$	-0.5,0.5	10,20,30,50	20	0.0
f_2	$f(x) = \frac{1}{4000}\sum_{i=1}^{d} x_i^2 - \prod_{i=1}^{d}\cos\frac{x_i}{\sqrt{i}} + 1$	-600,600	10,20,30,50	20	0.0
f_3	$f(x) = \sin^2(\pi w_1) + \sum_{i=1}^{D-1}[1 + 10\sin^2(\pi w_i + 1)] + (w_D - 1)^2[1 + \sin^2(2\pi w_D)]$ $(w_i = 1 + \frac{x_i - 1}{4})$	-10,10	10,20,30,50	20	0.0
f_4	$f(x) = \sum_{i=1}^{d} x_i^2 + (\sum_{i=1}^{d} 0.5ix_i)^2 + (\sum_{i=1}^{d} 0.5ix_i)^4$	-5,10	10,20,30,50	20	0.0
f_5	$f(x) = -\sum_{i=1}^{d}\sin x_i \sin^{2m}(\frac{ix_i^2}{\pi})$	0,π	10,20,30,50	20	0.0
f_6	$f(x) = -20exp(-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}) - exp(\frac{1}{n}\sum_{i=1}^{n}\cos 2(\pi)x_i) + 20 + e$	-32,32	10,20,30,50	20	0.0
f_7	$f(x) = 418.9829 * d - \sum_{i=1}^{d}(-x_i \sin\sqrt{abs(x_i)})$	-500,500	10,20,30,50	20	0.0
f_8	$f(x) = \sum_{i=1}^{d}(\lfloor x_i + 0.5^2 \rfloor)$	-100,100	10,20,30,50	20	0.0

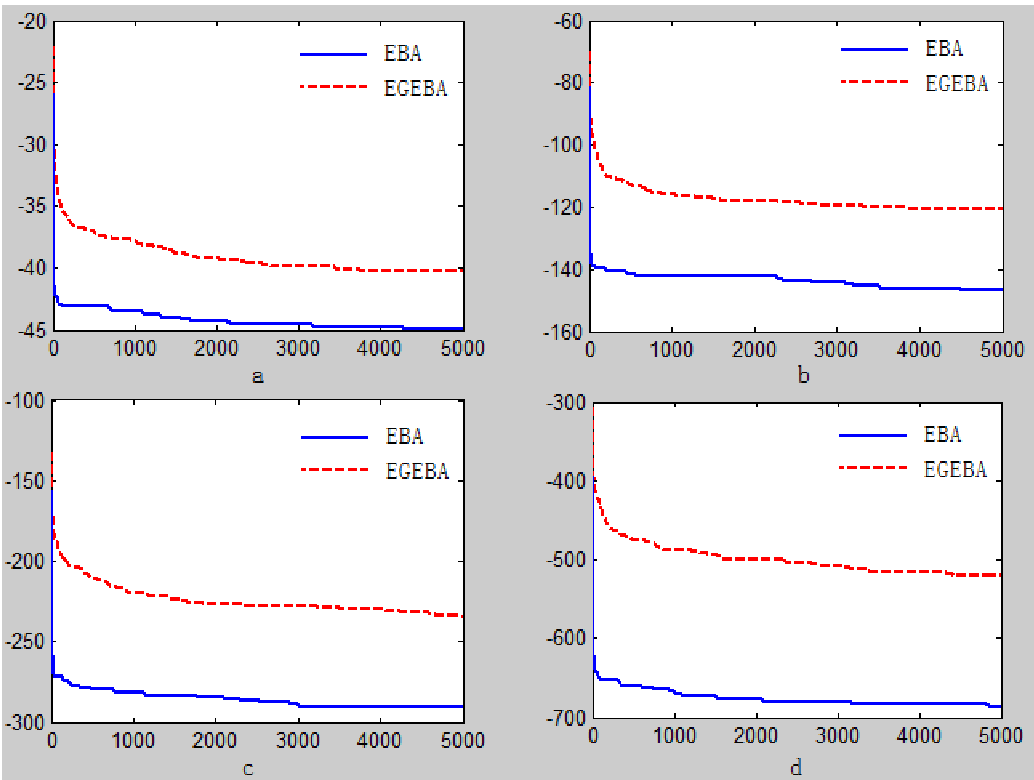

FIGURE 1. Experimental results of $f_1(x)$: a is 10 dimensions, b is 20 dimensions, c is 30 dimensions, and d is 50 dimensions

TABLE 2. The outcomes of the EGEBA and EBA on the testing functions

No.	D	EGEBA Best	EGEBA Worst	EGEBA Mean	EBA Best	EBA Worst	EBA Mean
f_1	10	-3.7946e+1	-4.5218e+1	-4.0332e+1	-3.7741e+1	-4.8985e+1	-4.4991e+1
	20	-1.1511e+2	-1.2660e+2	-1.2076e+2	-1.2646e+2	-1.6312e+2	-1.4707e+2
	30	-2.1768e+2	-2.6795e+2	-2.3488e+2	-2.5055e+2	-3.3020e+2	-2.9075e+2
	50	-4.6549e+2	-5.7045e+2	-5.2080e+2	-5.8537e+2	-7.5645e+2	-6.8606e+2
f_2	10	7.7700e-2	3.9778	1.0014	9.8610e-1	2.3006e+1	8.7115
	20	1.3500e-2	1.0031	1.3200e-1	5.1000e-3	1.5852e+1	1.3442
	30	2.8700e-2	1.4050e-1	7.2600e-2	9.9000e-3	1.5444e+1	3.6476
	50	5.7700e-2	2.3130e-1	9.3600e-2	9.7819	4.3424e+1	2.7736e+1
f_3	10	1.100e-02	2.2056	3.5220e-01	1.8240e-1	5.6612	1.7644
	20	1.0295	9.5985	4.1856	2.2294	1.5087e+1	5.6842
	30	3.8406	1.7057e+1	8.2454	4.1430	1.8674e+1	1.0148e+1
	50	1.3748e+1	4.1157e+1	2.7689e+1	9.9349	3.3382e+1	1.7133e+1
f_4	10	-4.2763e+1	-4.2796e+1	-4.2779e+1	-4.2804e+1	-4.2812e+1	-4.2807e+1
	20	-2.4508e+2	-2.5421e+2	-2.5415e+2	-2.4531e+2	-2.4536e+2	-2.4534e+2
	30	-7.5897e+2	-7.5923e+2	-7.5912e+2	-7.5956e+2	-7.5963e+2	-7.5959e+2
	50	-3.1497e+3	-3.1502e+3	-3.1499e+3	-3.1512e+3	-3.1513e+3	-3.1513e+3
f_5	10	-6.3839	-8.0722	-6.9634	-6.3971	-8.5146	-7.4986
	20	-6.4304	-9.2051	-7.9486	-8.0631	-1.2457e+1	-1.0154e+1
	30	-7.5604	-9.7062	-8.6395	-1.0221e+1	-1.5629e+1	-1.2384e+1
	50	-8.2918	-1.0924e+1	-9.7053	-1.3319e+1	-1.8111e+1	-1.5570e+1
f_6	10	1.8120e-1	5.2200e-1	4.2100e-1	5.1270	1.3873e+1	9.6522
	20	5.8590e-1	1.0889	9.3410e-1	9.2185	1.4745e+1	1.2409e+1
	30	1.0058	1.4128	1.3053	8.9853	1.5013e+1	1.2923e+1
	50	1.6850	1.6302e+1	2.9416	1.2300e+1	1.5930e+1	1.4189e+1
f_7	10	4.1798e+3	4.1798e+3	4.1798e+3	4.1798e+3	4.1798e+3	4.1798e+3
	20	8.3597e+3	8.3597e+3	8.3597e+3	8.3597e+3	8.3597e+3	8.3597e+3
	30	1.2539e+4	1.2539e+4	1.2539e+4	1.2539e+4	1.2539e+4	1.2539e+4
	50	2.0899e+4	2.0899e+4	2.0899e+4	2.0899e+4	2.0899e+4	2.0899e+4
f_8	10	2.1000e-2	5.1900e-2	3.8300e-2	0	1.0000e+2	7.32
	20	1.2930e-1	3.1270e-1	2.3760e-1	0	3.7000e+1	6.16
	30	5.0990e-1	7.1870e-1	5.9680e-1	0	1.1410e+3	3.9816e+2
	50	1.4407	1.8021	1.68	2.3910e+3	8.3640e+3	5.1251e+3

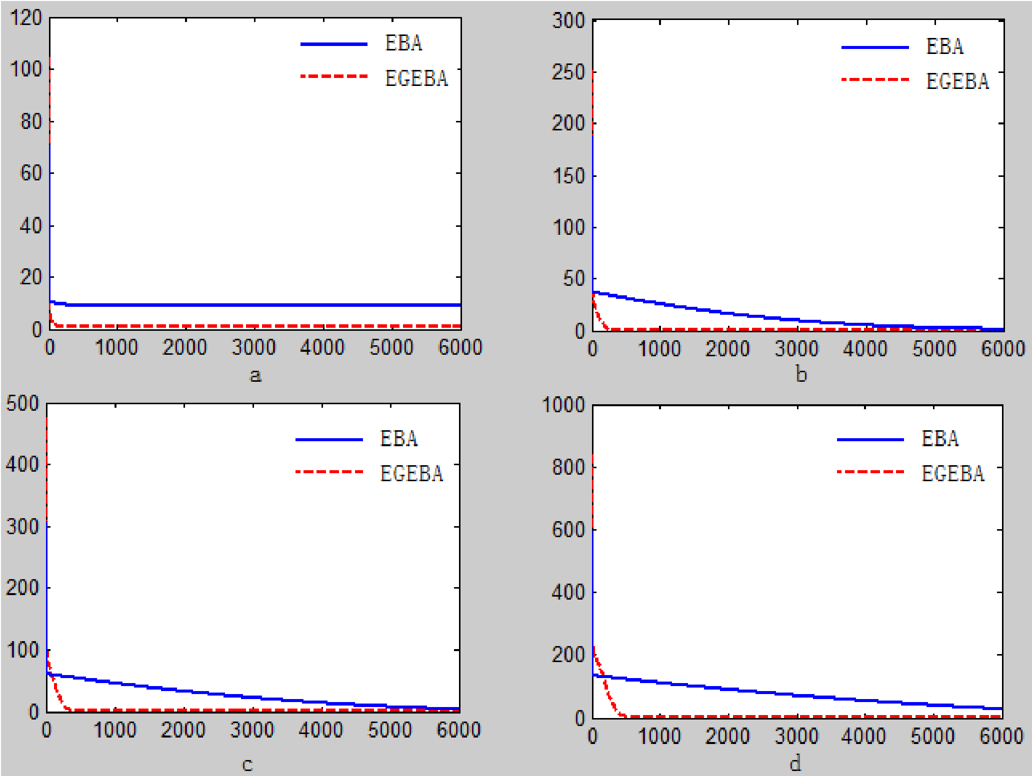

FIGURE 2. Experimental results of $f_2(x)$: a is 10 dimensions, b is 20 dimensions, c is 30 dimensions, and d is 50 dimensions

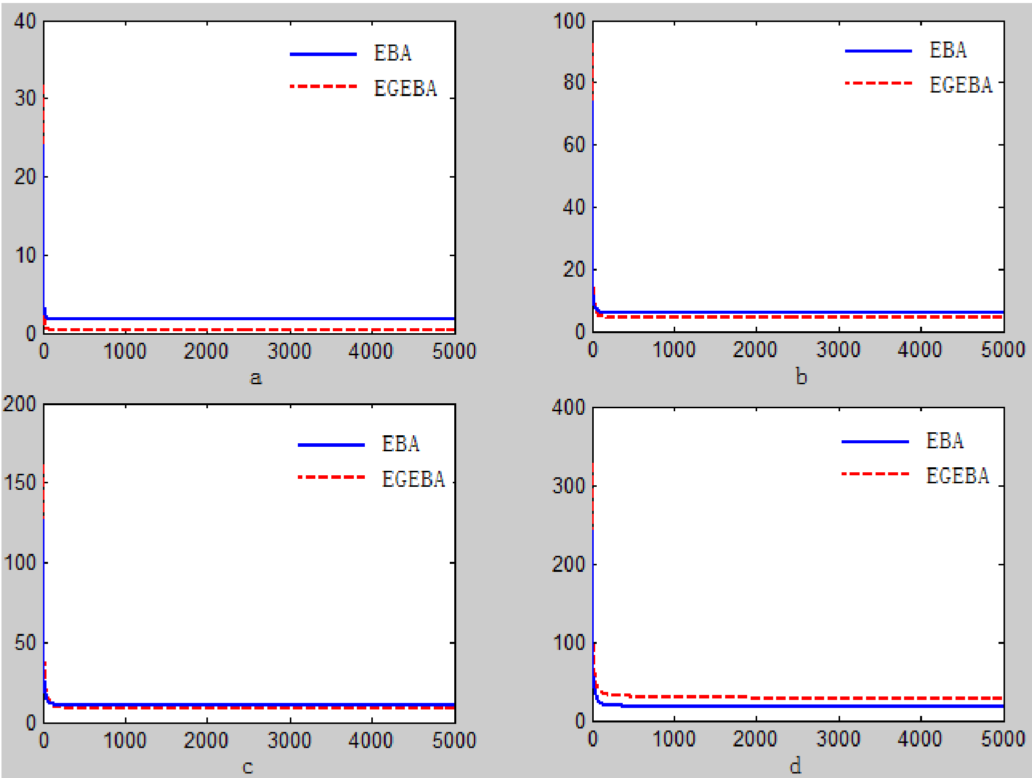

FIGURE 3. Experimental results of $f_3(x)$: a is 10 dimensions, b is 20 dimensions, c is 30 dimensions, and d is 50 dimensions

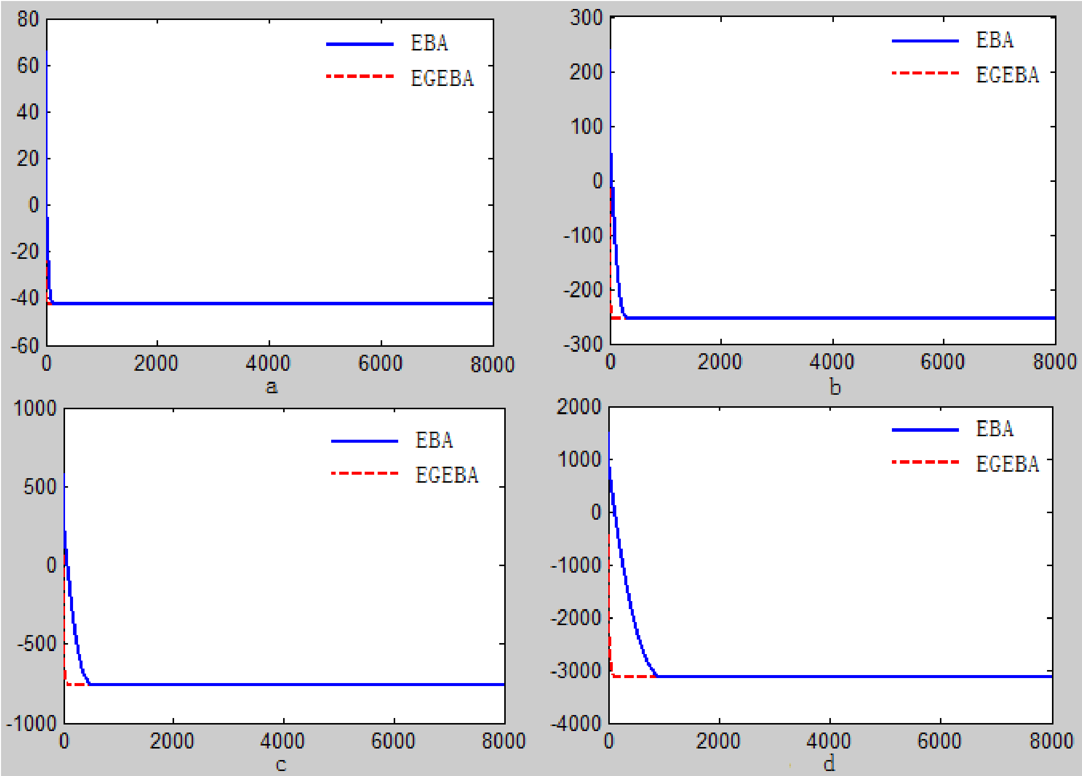

Figure 4. Experimental results of $f_4(x)$: a is 10 dimensions, b is 20 dimensions, c is 30 dimensions, and d is 50 dimensions

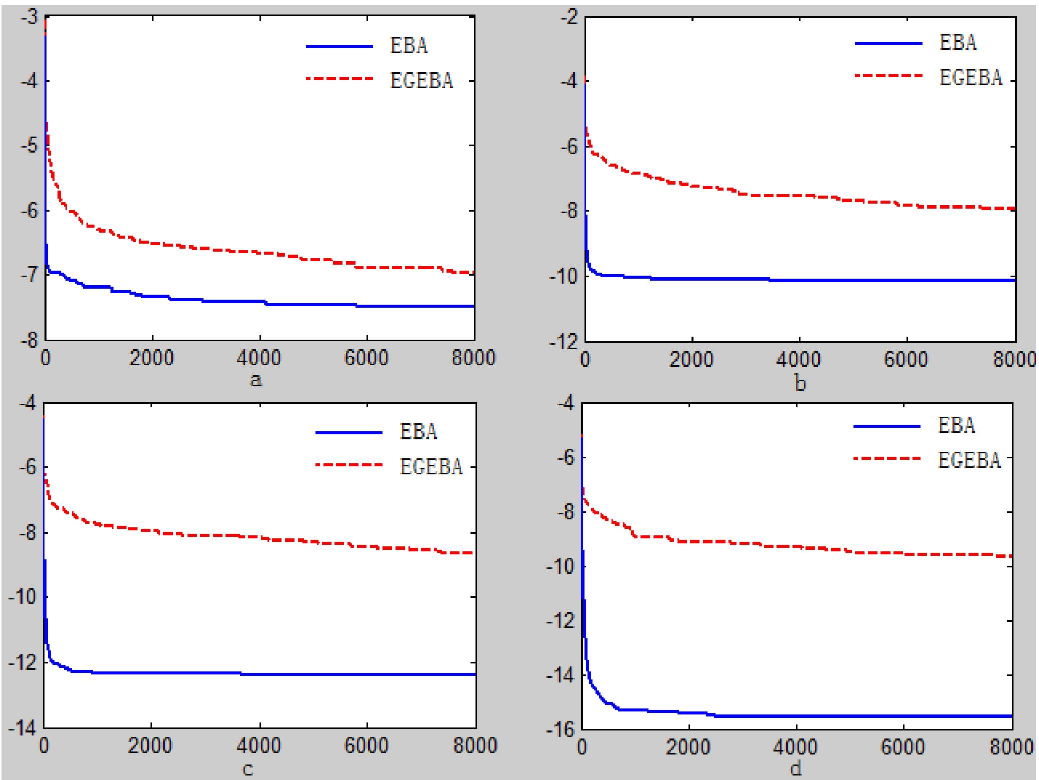

Figure 5. Experimental results of $f_5(x)$: a is 10 dimensions, b is 20 dimensions, c is 30 dimensions, and d is 50 dimensions

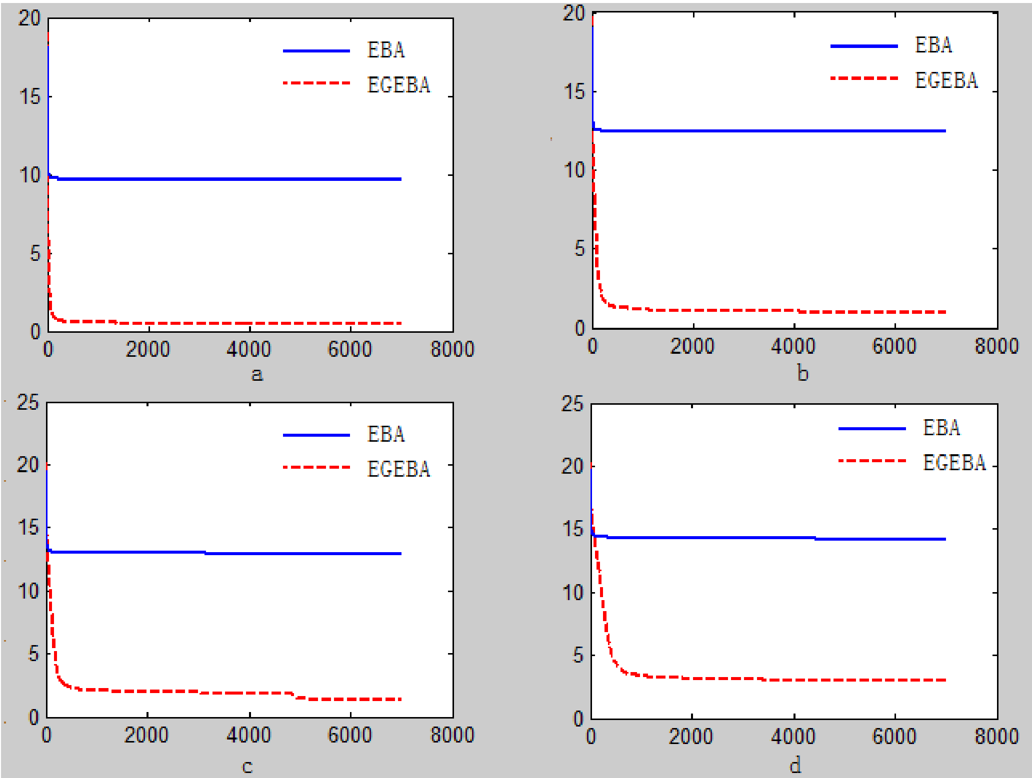

FIGURE 6. Experimental results of $f_6(x)$: a is 10 dimensions, b is 20 dimensions, c is 30 dimensions, and d is 50 dimensions

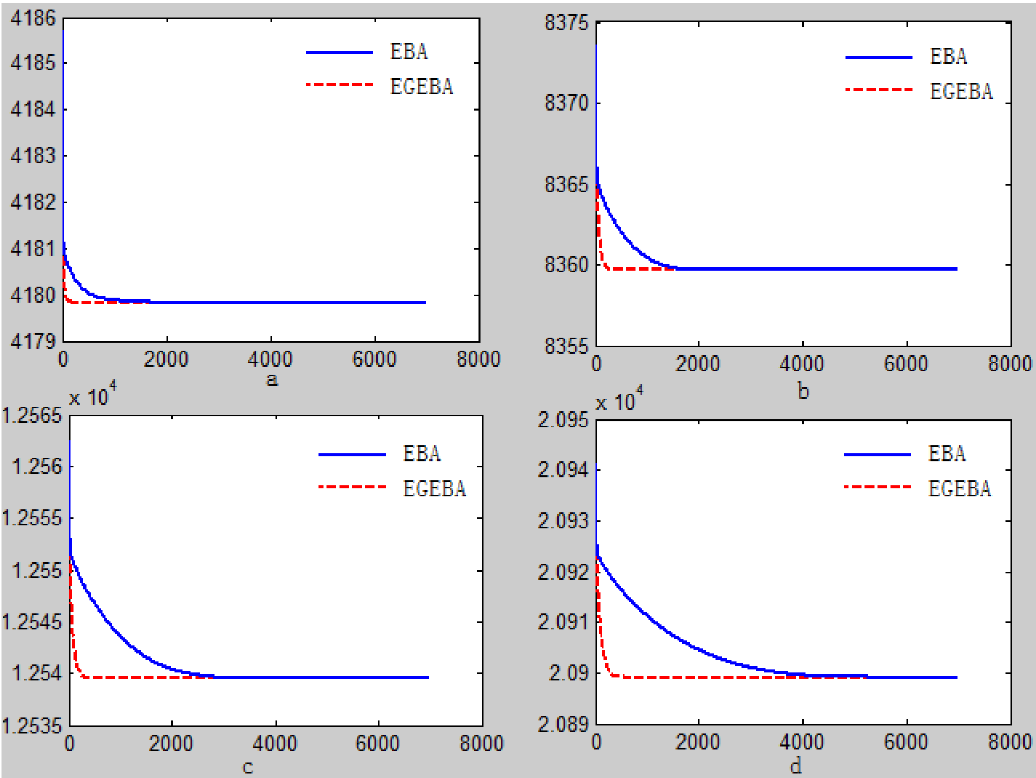

FIGURE 7. Experimental results of $f_7(x)$: a is 10 dimensions, b is 20 dimensions, c is 30 dimensions, and d is 50 dimensions

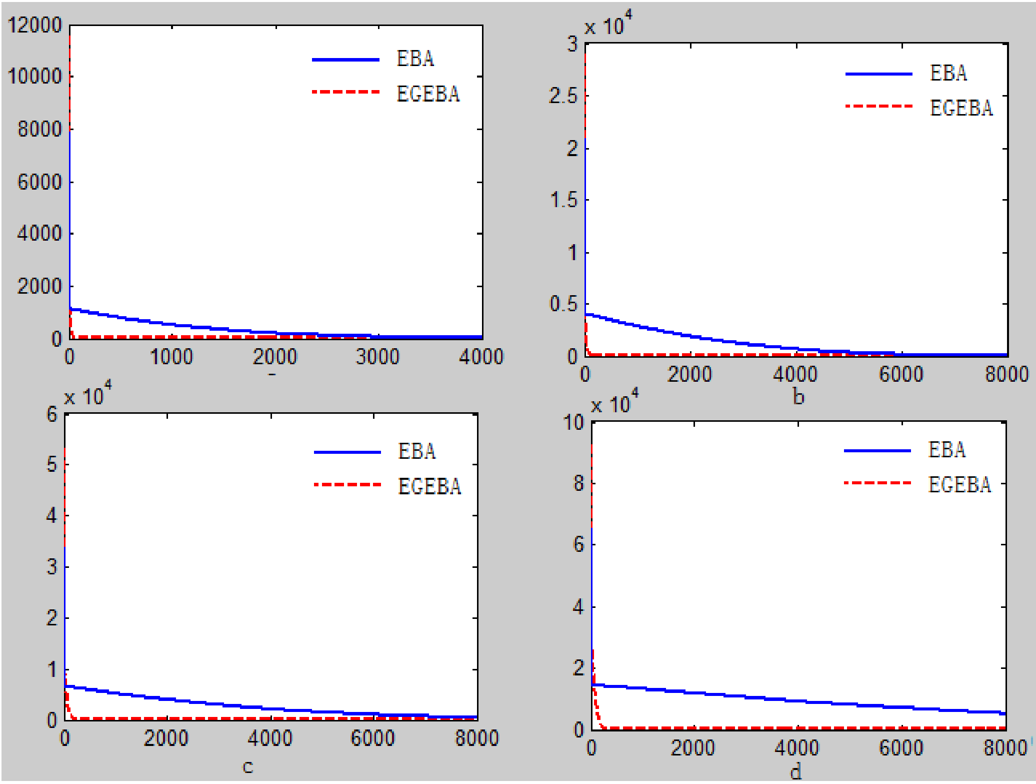

FIGURE 8. Experimental results of $f_8(x)$: a is 10 dimensions, b is 20 dimensions, c is 30 dimensions, and d is 50 dimensions

5. **Conclusions.** In this paper, a new bio-inspired algorithm "Echolocation Guided Evolved Bat Algorithm" is proposed. The bat's echolocation characteristic is introduced to EBA in this algorithm to avoid the blind search of a standard movement in EBA. The performance of the proposed algorithm is evaluated on well-known eight benchmark functions. The results state that, EGEBA provides better solutions with the same random processes. The echoic guide of standard movement is used to cope with the slow convergence, and the accuracy is improved too.

There are many issues worthy of further study, and many details might be considered in the future work of EGEBA. Our further work will focus on the two issues: on the one hand, the efficient EGEBA model should be developed depending on the analysis of real-world problems, and this model would be applied to solve specific engineering problems. On the other hand, how to overcome the local convergence is the next step of it workplan. We will do more diverse testing using more different fitness function sets, together with a detailed study of parameters.

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