ICIC Express Letters
Part B: Applications
Volume **7**, Number **7**, July **2016**

ICIC International ©2016 ISSN 2185-2766
pp. 1461–1466

UTILIZING DIRECTIONAL INFORMATION IN EVOLVED BAT ALGORITHM FOR GUIDING ARTIFICIAL AGENTS

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Received December 2015; accepted March 2016

Abstract. *In this paper, an idea of utilizing the directional information to guide the artificial agents in the searching process is led in to the Evolved Bat Algorithm (EBA). By properly using the directional information, the guided artificial agents can present higher searching accuracy than the agents in the conventional EBA. The advantage of our proposed method guides the artificial agent to cruise along the gradient information from the known near best solutions. It results in that the searching accuracy is increased with only a slight addition to the calculation. To test the accuracy on finding the near best solutions, 2 benchmark functions, whose global optimum are known, with different dimensional criteria are used in the experiments. The experimental results are compared with the conventional EBA under the same experimental conditions. The experimental results indicate that our proposed method improves the accuracy on finding the near best solution. According to the experimental results, our proposed Directional guided Evolved Bat Algorithm (DgEBA) is significantly improved compared with the conventional EBA.*
Keywords: Evolved Bat Algorithm, Swarm intelligence, Artificial agent, Optimization

1. **Introduction.** Different swarm intelligence algorithms are proposed one after another in recent years. Evolved Bat Algorithm (EBA) [15] series is one branch of swarm intelligence algorithm developed in 2012. The fundamental of EBA starts from the active sonar system, which is owned by the bats in the real world, in the basic physics. At the first beginning of when EBA is proposed, the movement of the artificial agent is designed with a fixed searching range per iteration. In addition, there is no guidance information from the other individuals or from the community. It implies that the conventional movement in EBA only employs the information from the individual itself, but not any support from the others. In this paper, we pull in the directional information from the community to guide the individual for moving forward to the discovered near best solution. The advantage gained by our proposed method increased the searching accuracy of EBA. The rest of the paper is composed as follows: the related work is briefly reviewed in Section 2, our proposed method is described in Section 3, the experiments and the experimental results are given in Section 4, and the conclusion is given at last.

2. **Literature Review.** Inspired by the tinny intelligent behaviors in biome, many swarm intelligence algorithms have been developed such as flower pollination algorithm [10], Artificial Bee Colony (ABC) algorithm [6], Particle Swarm Optimization (PSO) algorithm [7], firefly algorithm [19], and Bat Algorithm (BA) [18]. Optimization problem can be solved efficiently by these swarm intelligence algorithms. Algorithms in swarm intelligence are also employed to solve engineering problems in many different fields. For example, Cat Swarm Optimization (CSO) [5] series algorithm is successfully used in optimizing Artificial Neural Network (ANN) [20], Wireless Sensor Network (WSN) deployment [9, 11] and aircraft recovery problem [14]; EBA is used in constructing the recommended stock portfolio [3]; IABC is used in foreign exchange rate forecasting [1, 2], producing stock investment portfolio [4], and assisting the continuous authentication system [8, 13], as well.

In 2010, Yang proposes BA [18], which can be classified as one kind of swarm intelligence algorithms, presents preferable experimental result than PSO [7]. In BA, the artificial agents utilize the echolocation characteristics to locate their prey in the hunting behavior. Inspired by BA, Tsai et al. propose Evolved Bat Algorithm (EBA) [15] in 2012 by reconstructing the structure and the ways to move the artificial agents. The simplified control parameters are the most significant difference between EBA and BA. However, there are still some drawbacks in EBA. For example, the fixed constant used in the movement process for determining the step size of the artificial agent forms a limit boundary of the diversity of the artificial agents. In addition, the artificial agents are moved in the solution space without any guidance. It implies that the agents cannot converge to the global optimum. The limit caused by the fixed parameter is broken in a series of articles [12, 16, 17], but the drawback of lack of guidance information still remains unsolved. To overcome this drawback, the directional information is generated based on the experience gained by the artificial agents in their previous movements. And the directional information is used to navigate the artificial agents to cruise to the near best solutions. Using EBA in solving optimization problems, the parameter called the media should be defined as a constant. The chosen media has significant impact to the cruising range and the moving speed of the artificial agents in the solution space. It implies that this parameter is crucial to the exploration and exploitation capacity of the algorithm. The movement of the artificial agents in EBA can be described by Equations (1) and (2):

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

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

where $\triangle T \in [-1, 1]$ is a random variable, D denotes the distance between the current position to the prey, and x_i^t stands for a solution obtained by the ith artificial agent at the tth iteration.

Moreover, an optional process, which is also known as the random walk process, provides an opportunity for the artificial agents to further take one more step in the current iteration. Since the random walk process is deployed by chance, it implies that not all of the artificial agents are able to take the random walk process after the standard movement. Once an artificial agent gets the chance to execute the random walk process, its solution is updated by Equation (3):

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

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

In addition, the most significant difference between BA/EBA series algorithms and most of the swarm intelligence algorithms is that the greedy algorithm is employed in BA/EAB series algorithms. It implies that the artificial agents can only be migrated when the newly found solution provides better fitness value than the original one. However, the movement of the artificial agents is without guidance or any feedback information from the experience gained by the artificial agents.

3. **Our Proposed Method.** To allow the artificial agents being guided by the proper directional information, we propose a directional information guidance scheme for EBA [14], which is called Directional guided Evolved Bat Algorithm (DgEBA), in the searching process. In DgEBA, the random walk process is bound with the regular movement. In other words, the random walk process in DgEBA does not appear by chance, but must be executed after every movement. The movement process for the artificial agents in DgEBA can be processed by Equations (4) and (5):

$$x_i^{tmp} = x_i^{t-1} + D \tag{4}$$

where x_i^{tmp} represents the new location of the artificial agent after cruising a distance.

$$x_i^t = x_i^{tmp} + Dg \tag{5}$$

where Dg stands for the directional guided information from the known near best solution.

The guidance information is produced by Equation (6):

$$Dg = \begin{cases} \beta \cdot \left(x_{best} - x_i^t\right), & \text{if } fns_{new} = fns_{ori} \\ \alpha \cdot \left|x_{best} - x_i^t\right|, & \text{if } fns_{new} < fns_{ori} \\ -\alpha \cdot \left|x_{best} - x_i^t\right|, & \text{otherwise} \end{cases} \tag{6}$$

where α is a random number and $\alpha \in [0, 1]$; fns_{new} denotes the fitness value obtained by x_i^{tmp}, and fns_{ori} represents the fitness value calculated based on x_i^{t-1}.

The process of our proposed DgEBA is described as follows:

Step 1. Initialization: Randomly deploy the artificial agents into the solution space and calculate their fitness values by the fitness function.

Step 2. Movement: Calculate the cruise distance by Equation (1) and move the artificial agent by Equation (4). Determine the directional information by Equation (6), and then utilize the directional information to move the artificial agent by Equation (5). Evaluate all artificial agents and keep those present better fitness values than the original ones. The agents with worse fitness value give up the new solution and step back to where they were before the movement.

Step 3. Update: Update the kept near best solution if there exists a solution with better fitness value.

Step 4. Termination Checking: If the termination condition is satisfied, terminate the program and output the kept near best solution. Otherwise, go back to *Step 2.*

4. **Experiments and Experimental Results.** To test whether DgEBA presents higher accuracy in finding the near best solution and its convergence, 2 test functions with known global best solutions are employed in the experiment with different dimensions. We totally have 4 different dimensional conditions for all test functions. Hence, 8 sets of experimental results are obtained. The test functions used in our experiments are listed in Equations (7) and (8):

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

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

Each experiment is repeated 25 runs with different random seeds. The results are compared with EBA. For every test functions, the parameter n is set to 10, 30, 50, and

TABLE 1. Parameters for the experiments

	No. of Iteration	Population Size	Initial Range	Repeat Cycle
$f_1(X)$	6000	20	$[-600, 600]$	25
$f_2(X)$	7000	20	$[3, 13]$	25

100, respectively, to test the performance of DgEBA under different conditions. The values of the parameters used in the experiment are listed in Table 1.

Figure 1 and Figure 2 show the fitness values of the obtained near best solutions in all experiments. The unit on the x-axis is the iteration number, and the y-axis denotes the fitness value. While the dimensionality of the benchmark functions is decreased, the performance of our algorithm is increased. Moreover, the comparisons between DgEBA and EBA show that DgEBA presents better accuracy than the conventional EBA in the average results.

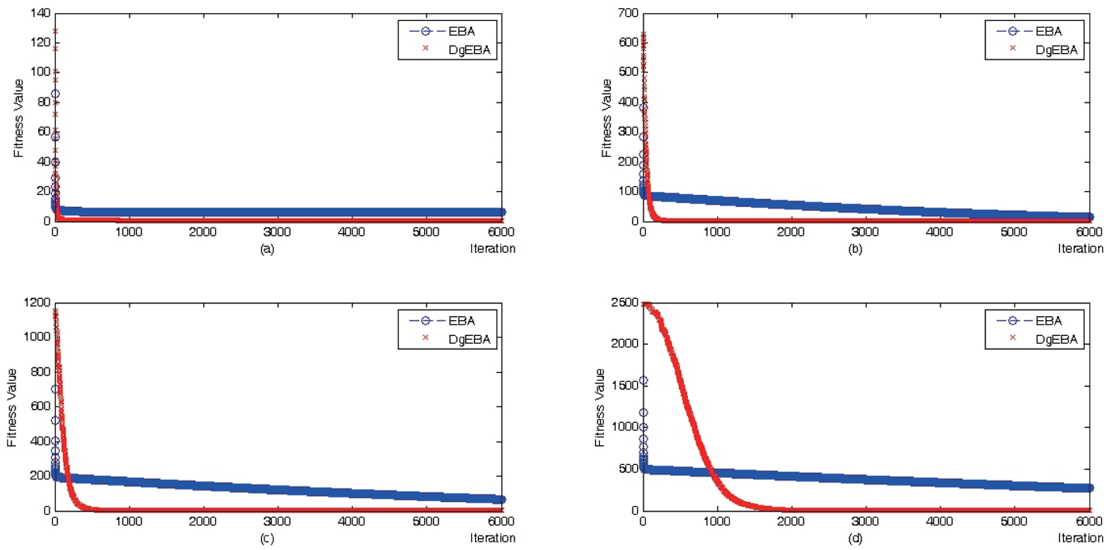

FIGURE 1. Experimental results of $f_1(X)$: (a) 10 dimensions, (b) 30 dimensions, (c) 50 dimensions, and (d) 100 dimensions

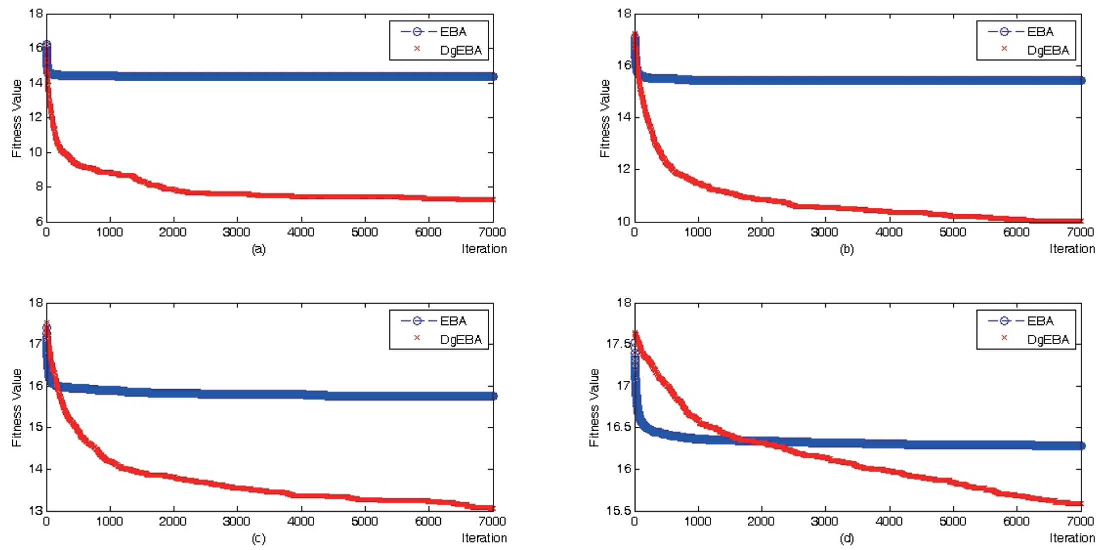

FIGURE 2. Experimental results of $f_2(X)$: (a) 10 dimensions, (b) 30 dimensions, (c) 50 dimensions, and (d) 100 dimensions

5. **Conclusions.** In this paper, we propose a new algorithm called DgEBA to solve numeric optimization problems. In our method, the directional information is obtained by either the experience gained by the artificial agent or by the near best solution. The experimental results indicate that DgEBA presents superior accuracy in finding the near best solutions than EBA. In the future work, we will focus on improving the searching accuracy by modifying the movement operation in DgEBA.

Acknowledgment. This work is partially supported by the Education Department of Fujian Province Science and Technology Project (JA13215), National NSF of China (No. 61201393, No. 61571139), New Star of Pearl River on Science and Technology of Guangzhou (No. 2014J2200085), and Prof. Jeng-Shyang Pan's Recruitment Program for Innovative Talents in Fujian University of Technology. The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

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