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# IMPROVING EVOLVED BAT ALGORITHM WITH AMPLITUDE MODULATION IN SWARM INTELLIGENCE

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Abstract. *In this paper, the amplitude modulation scheme from the conventional communication system is combined with Evolved Bat Algorithm (EBA) in order to amplify the diversity of the artificial agents in the searching process. By increasing the diversity of the artificial agents, the searching capacity of EBA is improved, accordingly. To test the accuracy on finding the near best solutions, 4 benchmark functions with known global optimum are used in the experiments. The experimental results are compared with EBA under the same experimental environments and the equal conditions. The experimental results indicate that our proposed scheme improves the accuracy on finding the near best solution about 37.207% in average. The minimum improvement is 7.282%; the maximum improvement is 99.942%. According to the experimental results, the improvement of EBA by our proposed scheme is significant.*

**Keywords:** Evolved Bat Algorithm, Swarm intelligence, Artificial agents, Optimization

1. **Introduction.** With the rapid improvement of computers in the computing power and the storage capacity, methods in soft computing become one of the options for finding solutions to engineering problems. Many methods, which are inspired by creatures in Mother Nature, in soft computing such as evolutionary algorithms and swarm intelligence are proposed one after another. For example, Chu et al. propose Cat Swarm Optimization (CSO) [5,6] for solving numerical optimization problems; Karaboga proposes Artificial Bee Colony (ABC) [7] based on simulating the behavior of honey bees; Yang proposes Bat-Inspired Algorithm (BA) by simulating the behaviors of bat hunting for its prey. Although the algorithms listed above present good performance in finding near best solutions, they still have some drawbacks that can be improved. Hence, Tsai et al. present the Enhanced Parallel Cat Swarm Optimization (EPCSO) [12] by parallelizing the structure of CSO and combining the Taguchi Method to improve the searching accuracy; Interactive Artificial Bee Colony (IABC) [13] is proposed to avoid the early convergence problem; Evolved Bat Algorithm (EBA) [14] is proposed to improve the performance of the original BA. The algorithms in swarm intelligence have also been employed to solve many engineering problems. For instance, CSO series algorithm is successfully used in optimizing Artificial Neural Network (ANN) [16], Wireless Sensor Network (WSN) deployment [9,10] and aircraft recovery problem [12]; IABC is used in foreign exchange rate

forecasting [1,2], producing stock investment portfolio [4], and assisting the continuous authentication system [8,11]; EBA is used in constructing the recommended stock portfolio [3] as well. Other applications with swarm intelligence can also be found in the literature [15]. When using EBA to solve numerical problems in optimization, we notice that the diversity of every artificial agent is not significant. Hence, we propose a strategy based on the amplitude modulation, which is involved in this work, to improve EBA on finding the near best solutions. The rest of the paper is composed as follows: the related work is briefly reviewed in Section 2, our proposed scheme is described in Section 3, the experiments and the experimental results are given in Section 4, and the conclusion is given at last.

2. **Review on Evolved Bat Algorithm.** In 2012, Tsai et al. present EBA by redesigning the operation of which BA generates new solutions. The most significant difference between EBA and BA is that the control parameters are much simplified in EBA. Based on the basic physics, the distance of which an artificial agent can cruise is estimated by the distance calculation in the active sonar system. To use EBA in solving optimization problems, a parameter, which stands for the media for transmitting the sound wave, should be set to a constant. The chosen media directly affects the cruising range and 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, $x$ stands for a solution obtained by the $i$th artificial agent, and $t$ identifies the number of current iteration.

Furthermore, an optional process, which is called the random walk process, provides an opportunity for the artificial agents to further cruise one more step in the solution space. The random walk process is deployed by chance. In other words, not all of the artificial agents are able to take the random walk process after the standard movement process. Once an artificial agent takes 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, $\beta$ 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/EBA 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.

3. **Our Proposed Scheme.** To improve the diversity of the artificial agents, we propose an amplitude modulation strategy for EBA in the searching process. The amplitude modulation is a signal modulation method widely used in the electronic communication fields. It utilizes an alternating-current signal to provide the carrier waveform, and the real signal (called the source modulation waveform) of which should be sent is involved in shaping the amplitude of the carrier wave. In general, the highest frequency of the modulating signal is less than 10 percent of the carrier frequency. The amplitude modulation technique can be commonly found in the conventional radio systems. A simple example

of the amplitude modulation is given as follows. Considering a cosine wave as the carrier wave of frequency $f_c$ and amplitude $A$ given by Equation (4):

$$c(t) = A \cdot \cos(2\pi f_c t) \tag{4}$$

where $c(t)$ denotes the carrier waveform and $t$ stands for the time.

In order to elaborate on the principle in a simple way, the source modulation waveform is chosen to be a cosine wave of a frequency $f_m$. The frequency of $f_m$ is much lower than $f_c$. The source modulation waveform is given by Equation (5):

$$m(t) = M \cdot \cos(2\pi f_m t) \tag{5}$$

where $m(t)$ represents the source signal and $M$ is the amplitude of the signal.

The output of the amplitude modulation result is depicted in Equation (6):

$$AM(t) = (1 + m(t)) \cdot c(t) \tag{6}$$

where $AM(t)$ stands for the output signal of the amplitude modulation result. Figure 1 shows an example of a source modulation signal, a carrier signal, and the amplitude modulation result.

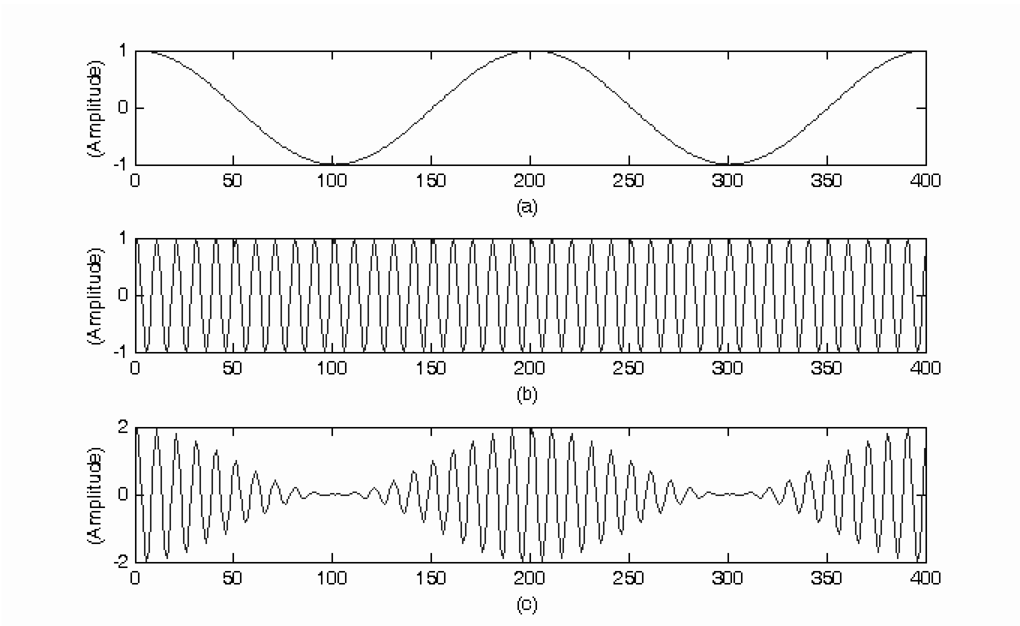


FIGURE 1. An example of the amplitude modulation: (a) source modulation signal, (b) carrier signal, (c) the amplitude modulation result

In our proposed scheme, an amplitude modulation signal is generated with pure cosine signals by Equations (4)-(6) with $f_m = 50$(Hz), $f_c = 1$(kHz), and $A = M = 1$. The iteration number is employed as $t$ for generating the waves. To include our proposed scheme in the process of EBA, the general movement of the artificial agent in Equation (1) is replaced by Equation (7):

$$D = AM \cdot \triangle T \tag{7}$$

To embed our proposed scheme in EBA, the process of the algorithm 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 (7) and move the artificial agent by Equation (2). Every artificial agent has a 50% chance to further take the random walk process by Equation (3). 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 the accuracy and the performance on finding the near best solution of our proposed scheme, 4 test functions are used in the experiment. The test functions are listed in Equations (8)-(11):

$$f_1(X) = 20 + e^1 - 20 \cdot e^{-0.2\sqrt{\sum_{i=1}^{n} \frac{x_i^2}{n}}} - e^{\sum_{i=1}^{n} \frac{\cos(2\pi \cdot x_i)}{n}} \tag{8}$$

$$f_2(X) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \tag{9}$$

$$f_3(X) = \sum_{k=1}^{n}\sum_{i=1}^{k} x_i^2 \tag{10}$$

$$f_4(X) = \sum_{i=1}^{n} x_i^2 - \sum_{i=1}^{n} \cos(2\pi \cdot x_i) + 10 \cdot n \tag{11}$$

The value of the parameters used in the experiment are listed in Table 1.

TABLE 1. Parameters for the experiments

| | Iterations | Population Size | Dimension | Initial Range | Repeats |
|---|---|---|---|---|---|
| $f_1(X)$ | $6 \times 10^3$ | $2 \times 10^1$ | $3 \times 10^1$ | $[-6 \times 10^2, 6 \times 10^2]$ | $2.5 \times 10^1$ |
| $f_2(X)$ | $5 \times 10^3$ | $2 \times 10^1$ | $3 \times 10^1$ | $[-3.2 \times 10^1, 3.2 \times 10^1]$ | $2.5 \times 10^1$ |
| $f_3(X)$ | $5 \times 10^3$ | $2 \times 10^1$ | $3 \times 10^1$ | $[3 \times 10^0, 1.3 \times 10^1]$ | $2.5 \times 10^1$ |
| $f_4(X)$ | $5 \times 10^3$ | $2 \times 10^1$ | $3 \times 10^1$ | $[-5.12 \times 10^0, 5.12 \times 10^0]$ | $2.5 \times 10^1$ |

Figure 2 shows the fitness value of the obtained near best solutions in all experiments. The unit of the $x$-axis is the iteration number, and the $y$-axis denotes the fitness value.

The final fitness values obtained in the experiments are listed in Table 2.

TABLE 2. Final fitness values obtained by EBA and EBA with our proposed scheme

| | $f_1(X)$ | $f_2(X)$ | $f_3(X)$ | $f_4(X)$ |
|---|---|---|---|---|
| EBA | $3.135 \times 10^1$ | $1.311 \times 10^0$ | $1.541 \times 10^1$ | $9.118 \times 10^1$ |
| EBA with our proposed scheme | $1.810 \times 10^{-2}$ | $1.133 \times 10^0$ | $1.429 \times 10^1$ | $6.563 \times 10^1$ |

According to the results listed in Table 2, our proposed scheme improves the final results obtained by EBA. The reason is that our scheme provides larger diversity to the individuals and increases both of the exploration and exploitation ability.

5. **Conclusions.** In this paper, we present an amplitude modulation scheme for improving the exploration and exploitation ability of EBA. The amplitude modulation signal can be calculated off-line. Hence, the computational complexity is still the same as the original EBA. To test the accuracy and performance on finding the near best solutions, 4 test functions are used in the experiments. The experimental results indicate that our proposed scheme improves the searching accuracy 37.207% in average. The minimum and the maximum improvements appear in test function $f_3$ and $f_1$, respectively.

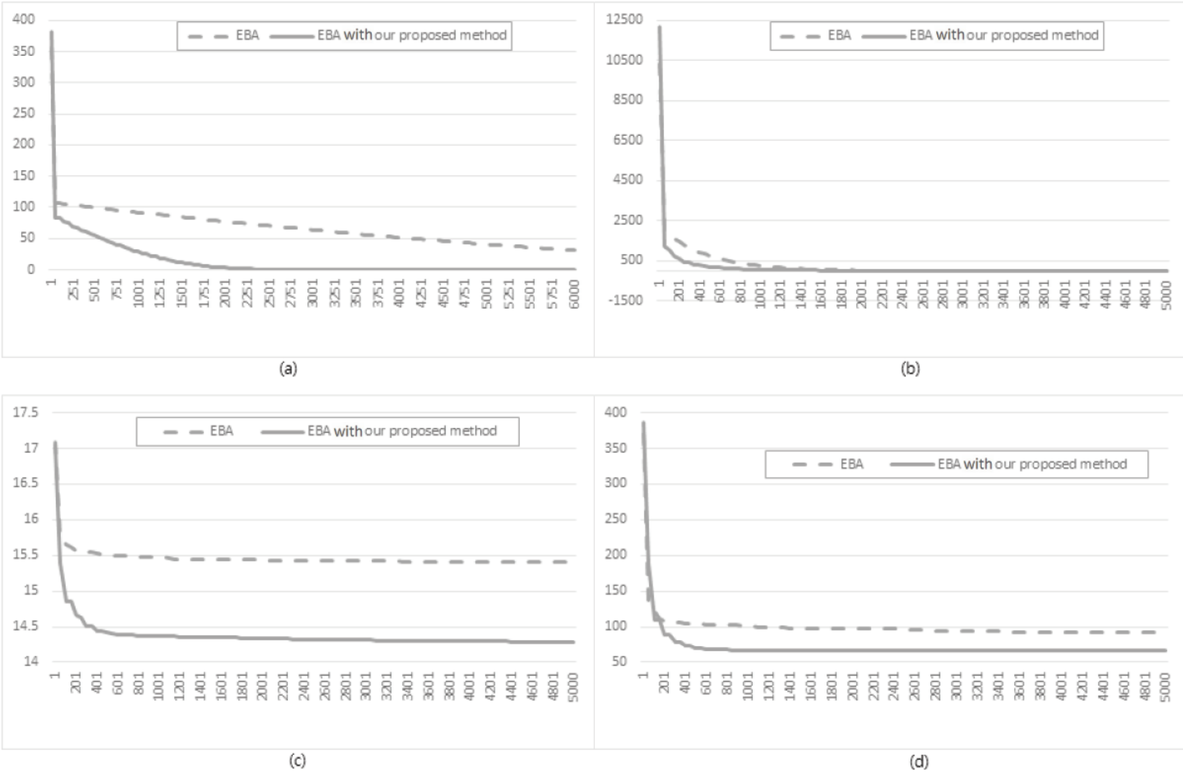


Figure 2. Experimental results of: (a) $f_1(X)$, (b) $f_2(X)$, (c) $f_3(X)$, (d) $f_4(X)$

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## REFERENCES

[1] J.-F. Chang, C.-T. Hsiao and P.-W. Tsai, Using interactive artificial bee colony to forecast exchange rate, *Proc. of the 2nd International Conference on Robot, Vision and Signal Processing*, Kitakyushu, Japan, pp.133-136, 2013.
[2] J.-F. Chang, P.-W. Tsai, J.-F. Chen and C.-T. Hsiao, The comparison between IABC with EGARCH in foreign exchange rate forecasting, *Proc. of the 1st Euro-China Conference on Intelligent Data Analysis and Applications*, Shenzhen, China, 2014.
[3] J. F. Chang, T.-W. Yang and P.-W. Tsai, Stock portfolio construction using evolved bat algorithm, *Proc. of the 27th International Conference on Industrial, Engineering & Other Applications of Applied Intelligent Systems*, Kaohsiung, Taiwan, 2014.
[4] J.-F. Chang, T.-W. Yang and P.-W. Tsai, Applying interactive artificial bee colony to construct the stock portfolio, *Proc. of the 2nd International Conference on Robot, Vision and Signal Processing*, Kitakyushu, Japan, pp.129-132, 2013.
[5] 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.
[6] S.-C. Chu, P.-W. Tsai and J.-S. Pan, Cat swarm optimization, *Lecture Notes in Computer Science*, vol.4099, pp.854-858, 2006.
[7] D. Karaboga, An idea based on honey bee swarm for numerical optimization, *Technical Report-TR06*, Erciyes University, 2005.
[8] M. K. Khan, P.-W. Tsai, J.-S. Pan and B.-Y. Liao, Biometric driven initiative system for passive continuous authentication, *Proc. of the 7th International Conference on Information Assurance and Security*, Malacca, Malaysia, pp.139-144, 2011.

[9] L. Kong, J.-S. Pan, P.-W. Tsai, S. Vaclev 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.

[10] 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 Trans. Systems, Man, and Cybernetics: Systems*, vol.44, no.1, pp.111-120, 2014.

[11] 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*, pp.1-11, 2012.

[12] 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.

[13] P.-W. Tsai, J.-S. Pan, B.-Y. Liao and S.-C. Chu, Enhanced artificial bee colony optimization, *International Journal of Innovative Computing, Information and Control*, vol.5, no.12(B), pp.5081-5092, 2009.

[14] P.-W. Tsai, J.-S. Pan, B.-Y. Liao, M.-J. Tsai and V. Istanda, Bat algorithm inspired algorithm for solving numerical optimization problems, *Applied Mechanics and Materials*, vols.148-149, pp.134-137, 2012.

[15] H. Yin, J. Q. Qiao, P. Fu and X. Y. Xia, Face feature selection with binary particle swarm optimization and support vector machine, *Journal of Information Hiding and Multimedia Signal Processing*, vol.5, no.4, pp.719-730, 2014.

[16] J. P. T. Yusiong, Optimizing artificial neural networks using cat swarm optimization algorithm, *International Journal of Intelligent Systems and Applications*, vol.1, pp.69-80, 2013.