Journal of **Software Engineering**

ISSN 1819-4311

Academic
Journals Inc.

www.academicjournals.com

OPEN ACCESS Journal of Software Engineering

ISSN 1819-4311
DOI: 10.3923/jse.2017.230.235

Research Article
An Improved Discrete Bat Algorithm Used for System Fault Diagnosis

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Abstract

Background: Traditional system fault diagnosis methods have low robustness. When it diagnoses system, the results are not accuracy. **Materials and Methods:** In this study, therefore, it proposes an improved discrete bat algorithm used for system fault diagnosis. The new algorithm includes three steps. Firstly, according to the actual meaning of system fault diagnosis, it adopts binary encoding to classify bat individuals. Secondly, it improves the fitness with a constraint equation. Thirdly, it applies a inertia coefficient into bat speed updating equation. Then it uses this new method to diagnose the system fault. **Results:** Finally, experiments show that the new algorithm can reduce the calculation difficulty, improve the diagnosis convergence speed and has higher diagnostic accuracy. **Conclusion:** The system fault diagnosis based on improved discrete bat algorithm is an effective method, which can effectively improve the accuracy of system fault diagnosis.

Key words: Discrete bat algorithm, system fault diagnosis, binary encoding, inertia coefficient

Received: October 02, 2016 Accepted: December 10, 2016 Published: March 15, 2017

Citation: Hang Li and Shoulin Yin, 2017. An improved discrete bat algorithm used for system fault diagnosis. J. Software Eng., 11: 230-235.

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Competing Interest: The authors have declared that no competing interest exists.

Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

System fault diagnosis model was first proposed by Preparata[1]. It can ensure system reliability, which has been used widely in many fields such as astronomical calculations, nuclear weapons research and online banking[2]. Also, there are many system fault diagnosis algorithms. Wang *et al*.[3] proposed a fault diagnosis strategy based on the principle component analysis and the multi-class Relevance Vector Machine. Sun *et al*.[4] developed a novel model-based fault diagnosis system. Fault signal of the motor was isolated with LRGF neural network online. Meanwhile, adaptive lifting scheme and adaptive threshold method were presented for detecting the faults from the isolated fault signal under the existence of mechanical error and electrical error. You *et al*.[5] presented a fault diagnosis approach of hydraulic system based on hybrid particle swarm optimization algorithm and wavelet packet energy entropy. What's more, genetic algorithm and firefly algorithm are used for system fault diagnosis. Although, it has high diagnostic accuracy, its time complexity is high too.

Bat Algorithm (BA) is designed based on the echo-location in the process of hunting for food. The BA is a kind of intelligent optimization search algorithm. It is implemented easily, can search optimal path. The BA combines some advantages of genetic algorithm, harmony algorithm and particle swarm optimization. So, it proposes an improved BA in this study for system fault diagnosis.

MATERIALS AND METHODS

Bat algorithm: The detailed Bat Algorithm (BA) is shown by Yang[6]. Position and speed updating Eq. 1-3 are as follows:

$$f_i(t+1) = f_{min}+(f_{max}-f_{min})\beta \tag{1}$$

$$V_i(t+1) = V_i(t)+(X_i(t)-X^*)\, f_i(t+1) \tag{2}$$

$$X_i(t+1) = X_i(t)+ V_i(t+1) \tag{3}$$

where, β is random number in [0, 1] with uniform distribution. $f_i(t+1)$ is the frequency of sound wave of i-th bat at t+1 time. f_{min} and f_{max} are the minimum and maximum of frequency of sound wave, respectively. The $V_i(t)$ and $V_i(t+1)$ are flying speed at t and t+1 time, respectively. The $X_i(t)$ and $X_i(t+1)$ are position at t and t+1 time, respectively and X* is global optimal bat at current population.

The BA selects a optimal solution (namely bat) to make position update with a certain probability from the existing solutions by simulating the bat. The position update way is Eq. 4:

$$X_{new} = X_{old}+\varepsilon A^t \tag{4}$$

where, $\varepsilon\in[-1, 1]$ is random number, X_{old} is current solution and A^t is the average value of current bat population loudness.

Generally, when in the process of bat on prey, if bat is closer to prey, the loudness is more lower. The frequency of pulse emission will gradually increase. Updating of pulse loudness and emission frequency are as Eq. 5 and 6:

$$A_i(t+1) = \alpha A_i(t) \tag{5}$$

$$R_i(t+1) = R_i(0)\times[1-e^{-\gamma t}] \tag{6}$$

where, $A_i(t)$ is the pulse loudness of i-th bat at t time. Initial pulse loudness ranges from [1, 2]. The $R_i(0)$ is the maximum emission frequency of i-th bat. $0<\alpha<1$ is pulse loudness attenuation coefficient and $\gamma>0$ is emission frequency increasing coefficient. When $t\to\infty$, $A_i(t)\to\infty$ and $R_i(t)\to R_i(0)$.

Improved discrete bat fault diagnosis algorithm

New population classification and initialization: In order to determine the unit state, according to the actual meaning of system fault diagnosis, it adopts binary encoding to classify bat individuals $X_i = (x_i^1,\ldots, x_i^N)$. Each bat is denoted by word string of length N. The $x_i^k = 1$ denotes that u_k is normal unit. $x_i^k = -1$ denotes that u_k is abnormal unit.

In this study, it divides the population into two types according to the number of individual, large population and small population. It uses different initialization methods for the two types. For large population, it adopts the method of Enright *et al*.[7]. And it adopts randomly generating way for small population. Each individual will be randomly allocated with 1 or -1.

The initial solutions obtained by large population initialization way are closer to final solutions, which effectively reduces the number of iteration and accelerates solving speed. But the initial solutions obtained by small population initialization way are relatively scattered avoiding that the initial solutions are concentrated in a small scope. The new initialization method not only ensures the quality of the population, but the diversity of the population.

New fitness algorithm: For the fitness of each individual in the group, fitness is solved by comparing the similarity level between compatible symptom F and target symptom G. So, the detailed fitness function is as following Eq. 7-10:

$$f(F, G) = \frac{\sum_{u_i \in U} f(F, G, u_i)}{N} \tag{7}$$

$$f(F, G, u_i) = \frac{f^{-1}(F, G, u_i) + f^{+1}(F, G, u_i)}{2} \tag{8}$$

$$f^{-1}(F, G, u_i) = \frac{|F^{-1}(u_i) \cap G^{-1}(u_i)|}{|d^{-1}(u_i)|} \tag{9}$$

$$f^{+1}(F, G, u_i) = \begin{cases} 1, f\ |d^{+1}(u_i)| = 0 \\ \dfrac{|F^{+1}(u_i) \cap G^{+1}(u_i)|}{|d^{+1}(u_i)|}, \text{ others} \end{cases} \tag{10}$$

Under PMC model, testing unit x_i^m, x_i^n and a_{mn} satisfy the following relationship as given in Eq. 11:

$$(x_i^m + 1)a_{mn}(a_{mn} - x_i^n) = 0 \tag{11}$$

It can use Eq. 11 to restrain fault sets. The new fitness method not only compares similarity level, but checks the condition in Eq. 11.

New speed updating strategy: In BA, inertia coefficient of flying speed is 1. However, it improves the speed updating strategy in this study: When bats are far away from the prey, bats need to keep a rapid movement to capture the prey; when bats are closer to the prey, bats need to use a relatively slower speed to gradually close to and capture prey. It introduces a inertial function coefficient to adjust bat's speed. So the improved speed updating Eq. 12 and 13 are as follows:

$$w_i(t) = e^{-\frac{25t}{t_{max}}} \tag{12}$$

$$V_i(t+1) = w_i(t)V_i(t)+(X^*-X_i(t)f_i(t+1) \tag{13}$$

where, X* is the lower fitness of current bat population. The speed in t+1 times is influenced by the speed, position, frequency and the optimal bat in population in t time. When X_i is far away from X*, X_i will move towards to X* with a fast speed, otherwise, it will move to X* with a low speed. If X_i is in the optimal position, the speed $V_i = 0$. Through Eq. 2, the function of $w_i(t)$ mainly adjusts the influence of previous speed $V_i(t)$ on current speed $V_i(t+1)$. The $w_i(t)$ is bigger, the influence caused by flying direction and impetus in last moment is bigger. The global optimization ability will enhance and local optimization ability will reduce. At the beginning of iteration, $w_i(t)$ is relatively big, which can avoid algorithm falling into local solution. Also, $w_i(t)$ will gradually decrease with the increase of iteration t. That can improve the convergence speed. In addition, it selects bat X° with low fitness value in current population to replace global optimal bat X* after each iteration and update speed. This process not only ensures that bats can fly to better solution, but bats also can fly to worse solution, which benefits the algorithm jumping out of local solution.

Bats discretization in addressing process: In continuous problem, bat algorithm utilizes the change of speed and position to realize its movement in search process. So position updating is easily achieved by adding speed in original position as Eq. 3. However, system fault diagnosis problem belongs to discrete problem, general BA cannot execute discrete search, so it needs to use speed of bat to transform position into 1 or -1. In other words, it must design a link between speed and position. In this study, it presents that the speed of each bat corresponds to a probability. Bat's position is closely related to the probability value. When the absolute value of bat's speed reduces gradually, the probability decreases too. If the speed reaches to 0, then the probability is 0 too. It sets parameter: $S(V_i) = (S_i^1, \ldots, S_i^N)$

$$S_i^k(t) = \begin{cases} \dfrac{2}{1+e^{-5V_i^k(t)}} - 1, \ V_i^k(t) > 0, \\ 1 - \dfrac{2}{1+e^{-5V_i^k(t)}}, \ V_i^k(t) \le 0 \end{cases} \tag{14}$$

Then it uses $S(V_i) = (S_i^1, \ldots, S_i^N)$ to adjust position of X_i:

$$X_i^k(t+1) = \begin{cases} -X_i^k(t), \text{ rand} \le S_i^k(t+1) \\ X_i^k(t), \text{ rand} > S_i^k(t+1) \end{cases} \tag{15}$$

where, Eq. 14 is the function that maps the speed of bat as position changing probability, $S_i^k(k = 1, 2, \ldots, N)$ is the changing probability of bat.

Detailed process of improved discrete bat:

Step 1: Initializing individual position X_i and parameter: $A_i(0)$, $R_i(0)$ f_{max}, f_{min}, V_i, α, γ, t. According to Eq. 7-11, setting fitness function $f(X_i)$

Step 2: Computing fitness according to Eq. 8 and finding optimal bat X*

Step 3: Judging stopping condition. If YES. Return to step 11, otherwise t = t+1

Step 4: If t%gen = 0, updating speed V_i of i-th bat according to Eq. 1 and 14. Otherwise, updating speed V_i of i-th bat according to Eq. 1 and 13

Step 5: If $V_i>V_{max}$, then $V_i = V_{max}$. If $V_i>V_{min}$, then $V_i = V_{min}$

Step 6: According to Eq. 14 and 15, making binary mapping for speed and getting X_{new}

Step 7: If rand>r_i, probability is 0.5 to change position. And form a local solutions around optimal solutions

Step 8: Checking diagnosable constraints

Step 9: If rand<A_i and $f(X_{new})<f(X^*)$, then $X_i = X_{new}$. According to Eq. 5 and 6, updating pulse launching frequency R_i and sound loudness A_i of bat

Step 10: Finding current optimal bat X* and return to step 3

Step 11: Output current optimal solutions

RESULTS AND DISCUSSION

It makes experiments under MATLAB platform. In order to verify effectiveness of our new algorithm, it also makes comparison to bat algorithm. System unit number N is 100 and 500, iteration number is 1000 and 4000, respectively. The fault unit number ranges from 1 to N/2-1. Size of population is 30. The α∈[0.8, 1], γ∈[0.7, 1], $A_i(0)$∈[1.5, 2], R(0)∈[0.8, 1], f_{max} = 1, f_{min} = 0. Figure 1 is the comparison of Bat Algorithm (BA) and Improved Bat Algorithm (IBA) including average iteration number (A), average accuracy (B) and optimal average fitness value (C).

It can know that iteration number of Improved Bat Algorithm (IBA) is obviously less than that of BA. And the difference between these two algorithms gradually increases with the increase of fault unit number. The optimal fitness value (diagnostic accuracy) with IBA is superior to BA as in Fig. 1. When N = 500, the results are also accuracy as Fig. 2.

Then it makes experiments about influence of parameter α, γ and $A_i(0)$ on system fault diagnosis. For α, it fix other parameters and change α. The result is as Fig. 3. With the increase of α, the iteration number reduce, but average accuracy and optimal average fitness value increase.

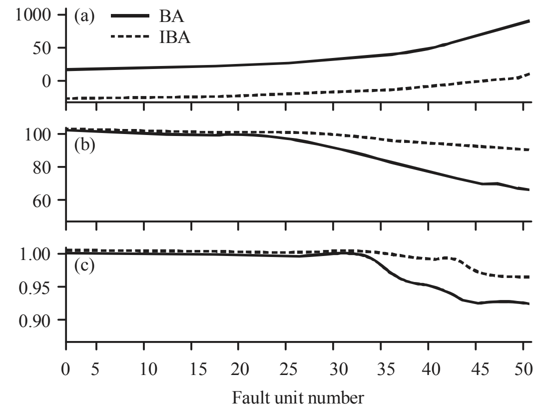

Fig. 1(a-c): Comparison of diagnosis results, N = 100

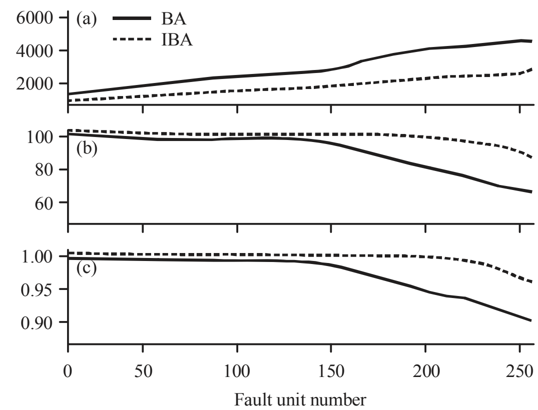

Fig. 2(a-c): Comparison of diagnosis results, N = 500

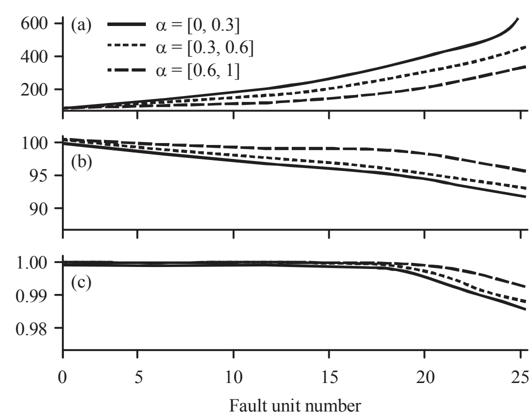

Fig. 3(a-c): IBA performance with different α

Meanwhile, it adopts similar method to test γ and $A_i(0)$ as Fig. 4 and 5. From the Fig. 4 and 5, it can know that the performance of IBA with different γ and $A_i(0)$ has similarity on the changing trend. So when the value of α, γ is close to 1 and the value of $A_i(0)$ is close to 2, the performance of IBA is better. Finally, the system diagnosis effect is also better.

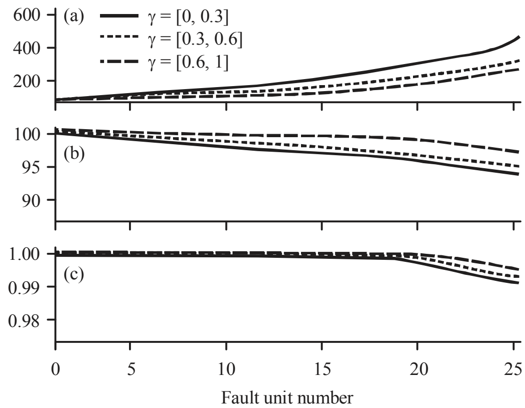

Fig. 4(a-c): IBA performance with different γ

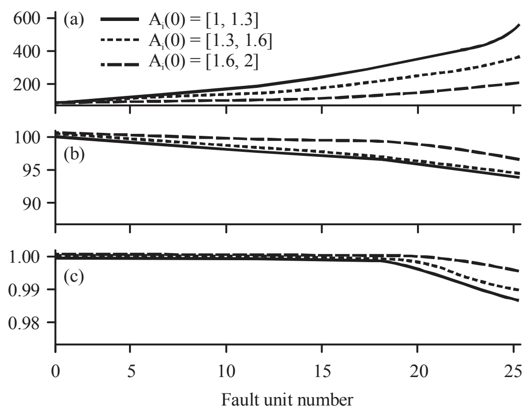

Fig. 5(a-c): IBA performance with different $A_i(0)$

At present, system fault diagnosis is a hot issue. Many researchers have done studies for it. For example, in study of Cui *et al.*[8], the probabilistic derivation of diagnosability was presented for the faults containing uncertainties and a method for analyzing system-level quasi real-time diagnosability was given. The stochastic characterizations of different fault modes were extracted and a measurement based on the modified distance was established to quantify diagnosability performance. Shen *et al.*[9] presented a time delay due to fault diagnosis. First, a fault diagnosis model was constructed to diagnose sensor faults which integrate time-varying gain and bias faults, where a novel fault diagnosis algorithm was proposed, which removed the classical assumption that the time derivative of the output error should be known. Second, the time spend at each step in fault diagnosis and its analytical expression were derived strictly. Paulson *et al.*[10] described an input design method to actively isolate faults for polynomial or rational systems in the presence of unknown-but-bounded uncertainties. It proposed to replace the inner program with a convex relaxation that could be efficiently solved while still guaranteeing fault detection and isolation. The approach was numerically demonstrated on a two-tank system with three fault models. Comparing the simulation results with the theoretical analysis, this new method can effectively improve the accuracy of system fault diagnosis.

CONCLUSION

This study propose an improved discrete bat algorithm used for system fault diagnosis. The initialization way of improved algorithm can ensure the diversity of population. New speed updating equation can better adjust global and local search which can effectively reduce precocity phenomenon. New fitness function can avoid generating redundant compatible fault mode, which improves the convergence speed. Finally, experiments show that the new method has high calculation accuracy and better global search ability. In the future, it will further improve this method and study more advanced system fault diagnosis methods to apply them into practical engineering applications.

ACKNOWLEDGMENT

The authors would like to thank the anonymous referees for constructive suggestions. This study is supported by National Scientific Foundation (No. 60970112).

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