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# An Improved Artificial Bee Colony Algorithm for Staged Search

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***Abstract***

*Artificial Bee Colony(ABC) or its improved algorithms used in solving high dimensional complex function optimization issues has some disadvantages, such as lower convergence, lower solution precision, lots of control parameters of improved algorithms, easy to fall into a local optimum solution. In this letter, we propose an improved ABC of staged search. This new algorithm designs staged employed bee search strategy which makes that employed bee has different search characters in different stages. That reduces probability of falling into local extreme value. It defines the escape radius which can guide precocious individual to jump local extreme value and avoid the blindness of flight behavior. Meanwhile, we adopt initialization strategy combining uniform distribution and backward learning to prompt initial solution with uniform distribution and better quality. Finally, we make simulation experiments for eight typical high dimensional complex functions. Results show that the improved algorithm has a higher solution precision and faster convergence rate which is more suitable for solving high dimensional complex functions.*

***Keywords:*** *artificial bee colony, staged search, function optimization, escape radius, uniform distribution, backward learning*



## 1. Introduction

As we all know, Artificial Bee Colony (ABC) [1, 2] is an intelligent optimization algorithms imitating bees foraging in the nature, which has the character of easily implement and setting parameters. State-of-the art of the field the report is that artificial bee colony can be used for anomaly-based intrusion detection systems. Also an artificial bee colony algorithm is presented for data collection path planning in sparse wireless sensor networks. ABC algorithm is used for function optimization and combines genetic algorithm, particle swarm algorithm and finite difference algorithm to solve some complex problems especially TSP problems [3, 4]. ABC algorithm also is used in neural network training and digital IIR filter designing.

However, in the practical engineering application, many production practice problems are transformed into high dimensional complex function optimization problems. But it has characters of function complex, great scale, high dimensions and nonlinear. When we use classical optimization method to solve this question, it is easy to fall into local extremum with the increase of dimension. ABC exists some disadvantages, such as premature convergence, easy to fall into local extremum and low solution. So Mansouri [5] proposed a novel iterative method combining ABC and Bisection method to find the fixed point of a nonlinear function effectively. Imanian [6] proposed a modified ABC algorithm called VABC to overcome this insufficiency by applying a new search equation in the onlooker phase. It used the PSO search strategy to guide the search for candidate solutions. Wang [7] proposed a novel multi-strategy ensemble ABC algorithm. A pool of distinct solution search strategies coexisted throughout the search process and competed to produce offspring. Mustafa [8] proposed integration of multiple solution update rules with ABC which used five search strategies and counters to update the solutions. P. Mustafa [9] added directional information to ABC algorithms. The new scheme was compared with basic ABC and ABCs with MR. It examined the performance of this method on well-known nine numerical benchmark functions to show it effectively.

The above improved ABC algorithms achieve good effect, But they also has some disadvantages with more control parameters, premature convergence et al. To solve those

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questions and improve solution precision and convergence speed of ABC algorithm, we propose an improved staged search Artificial Bee Colony (SSABC) algorithm. This new scheme adopts initialization strategy based on uniform distribution and backward learning. It improves the quality of initial honey and enhances global searching ability of bee colony. We divide employed bee search behavior into two stages. The two stages use different search strategy which improves the solution precision and convergence speed of ABC algorithm. The following bee uses adaptive optimization strategy to enhance production ability of following bee. We define the escape radius to guide escape direction of precocious individual which reduces blindness of individual escape effectively. Our main contribution is that we improve the employee bees, following bees and scouts respectively. Then experiments results show that our new method has high efficiency than original ABC. The following is the structure of our paper. The next section is the detailed improved ABC algorithm. Section 3 is the experiments results. The last section is a conclusion.

## 2. The Improved Staged Search Artificial Bee Colony

### 2.1 Uniform Designing and Backward Learning for Initialization Strategy

The initial honey is the algorithm search origin. In ABC algorithm, initial honey is produced randomly (i.e. it generates several individual to form initial group). If the initial group is generated unreasonably. It will have an effect on the ability of global optimization. So we must improve the generation method of initial group to make the initial individual distribution uniformly and has a better quality. Reference [10] adopts uniform to design and initialize the group. It ensures the initial nectar source distributed within the search space uniformly. But it cannot ensure that nectar source is good. If ABC uses initialization strategy based on backward learning, it will ensure the quality of nectar source and cannot ensure the uniform distribution. So this letter combines backward learning and uniform designing. The detailed processes are as follows.

a) We uniformly divide the value range of preparative optimization into *SN* subspaces. It will randomly produce an initial solution from every subspace and form initial individual as Equation (1).

$$x_{i,j}^{sn} = x_{\min,j}^{sn} + ran(0,1)(x_{\max,j}^{sn} - x_{\min,j}^{sn}) \tag{1}$$

b) It solves reverse solution of each initial solution $Ox_{i,j}^{sn}$ as Equation (2).

$$Ox_{i,j}^{sn} = x_{\min,j}^{sn} + x_{\max,j}^{sn} - x_{\min,j}^{sn} \tag{2}$$

Where $x_{i,j}^{sn}$ denotes *i-th (1≤i≤SN)* nectar source and *j*-dimension *i-th(1≤j≤D)* coordinate at *sn-th(1≤sn≤SN)* subinterval. $x_{\min,j}$ and $x_{\max,j}^{sn}$ are minimum nectar source and maximal nectar source respectively.

### 2.2. Staged Employed Bees Search Strategy

In the early stage of solving problem, hire bees search behavior should have stronger searching ability and fully explore the search space. It makes a good preparation for subsequent following bees mining activities. In the late stage of solving problem, algorithm converges to global optimal solution. Hire bees should have stronger searching ability and improve the convergence rate of problem. In order to better accommodate the search request of employed bee, this paper designs a staged employed bees search strategy. First stage: hire bees search behavior should have stronger exploration competence which can fully explore the search space and accelerate the emergence of global optimal solution; Second stage: hire bees search behavior should have stronger mining ability and promote the convergence rate of algorithm. The detailed processes are as follows:

a) At first stage, we use Equation (3) to search.

$$v_{i,j} = x_{i,j} + \beta(x_{i,j} - x_{k,j}) + \varphi(x_{best,j} - x_{r,j}) \quad (3)$$

Where β is a random number of [-1,1]. φ is a random number of [-1,1]. $x_{best,j}$ is j-dimension coordinate of current global optimal solution, *k≠r≠i*. Because it adds the optimal position $x_{best,j}$, it improves the mining ability to some extent.

b) Second stage. Strength of hire bees mining ability has an effect on the convergence rate of algorithm. So this paper proposes an adaptive search strategy as shown in (4).

$$v_{i,j} = x_{i,j} + \omega \times (1 - \lambda \frac{t}{t_{\max}}) \times (x_{best,j} - x_{i,j}) \quad (4)$$

Where $t_{max}$ is the maximum number of iteration. $t$ is the beginning iteration number of second stage. $w$ is a random integer number of [-1,1]. λ is a random number of (0,1). $w$ can ensure that the search range is not limited to the direction of $(x_{best,j} - x_{i,j})$. It can search the neighborhood of $x_{i,j}$ roundly. λ prevents tending to zero at the end of iteration algorithm. $\omega \times (1 - \lambda \frac{t}{t_{\max}})$ will increase with the increasing of $t$. Search range of colony reduces gradually and production ability of hire bee strengthens gradually.

c) If the function value of food source $V_i$ is superior to $X_i$, then $V_i$ will replace $X_i$.

### 2.3. Following Bee Strategy of Adaptive Local Search.

At search stage, following bee selects better nectar source to explore and develop again. So following bee search should have strong ability of production. Meanwhile, in order to fall into local minima value, it also should have exploration ability. Based on optimization characteristic of following bee, we design a following bee strategy of adaptive local search.

1) According to the probability selection formula $P_i$ of ABC algorithm, following bee selects nectar source $X_i$ to search optimizing. $f_i$ is search function. $P_i$ can be calculated by:

$$P_i = f_i / \sum_{i=1}^{SN} f_i \quad (5)$$

2) According to (4), we start local search ($t$ is current iteration number).

3) When following bee begins local search, hire bee researches nectar source in stages to improve convergence rate, keep population diversity and jump out of local optimum.

4) It compares the new nectar source $V_i$ of following bee, new nectar source $V'_i$ of hire bee and old nectar source $X_i$ and selects nectar source with better fitness value as new nectar source.

### 2.4. Escape Scouter Strategy

In ABC algorithm, scouter is in charge of finding the premature convergence individual and updating algorithm which can reduce the probability of premature convergence. Because the existing ABC algorithms [11-13] have the defect of restricting the escape of precocious individual [13]. We deign a new escape scouter strategy. If $X_i$ is precocious individual. Then it shows that $X_i$ falls into local extremum with itself as center and ε as radius. We define neighborhood range as extremum neighborhood which results in individual falling into local extremum. Radius ε of extremum neighborhood is escape radius of $X_i$. $X_i$ needs to jump out of local extremum point, it must make the Xi escape extremal neighborhood. The detailed strategy is as below:

Step 1. Setting main initial parameters: the number of population (*SN*), maximum cycle times (*maxCycle*), parameter dimension (*D*), mining bees and observation bees represent about 50 percent of total. One scout bee.

Step 2. Executing the initialization strategy of uniform distribution-reverse learning.

Step 3. Calculating fitness value of initial population and recording current optimal solution.

Step 4. Executing hire bee search strategy in stages and recording the current optimal solution.
Step 5. Executing following bees strategy of adaptive local search.
Step 6. If there exists renunciative nectar source, then mining bee will be changes as observation bees in this area. It will produce new nectar source according to the escape scouts search strategy and calculate fitness value. Global optimal solution will be stored.
Step 7. Adding cycle times. Determining if it is greater than maxCycle. If YES, then go to step8. If NO, then back step4.
Step 8. Reaching maxCycle and discontinuing algorithm. It will output global optimal solution.

## 3. Simulation Results and Analysis.

In order to verify the superiority of this algorithm, we select ESABC (Elite Swarm ABC) algorithm, MABC (Modified Artificial Bee Colony) algorithm, ABCMSS (Artificial Bee Colony Algorithm with Modified Search Strategy) algorithm to compare. $SN = 40, maxCycle = 1000, D = 200$.

Algorithm runs independently 50 times under MATLAB platform. Table1 shows eight high-dimensional complex functions optimization computing results by the four algorithms. We use the text functions in table1 to test performance for the four algorithms. And we evaluate this algorithm from mean, standard deviation, the optimal value, the worst value and average time cost five aspects. Mean value and optimal value can represent the convergence precision and optimization capability of algorithm. From Table 1, we can know that when solving high-dimensional (200) unimodal optimization problem, SSABC algorithm is remarkably higher than other three algorithms. SSABC algorithm almost finds the theoretical optimal solution for Sphere function (Reaching 10-95) and Sumsquares function (Reaching 10-86). Optimization precision of this two functions can reach 10-170. SSABC gets the same effect for high-dimensional multi-modal function: Griewank function, Rastrigin function and Ackley function. It conducts fifty optimization experiments and the three functions reach 10-16. For Rosenbrock function, Schwefel2.26 function, Zakharov function, due to their own features, the algorithm easily falls into local extremum value. But SSABC still obtains ideal solution. So we can conclude that SSABC algorithm shows good ability of mining and exploration, it is more suitable for solving high-dimensional complex optimization problems. Standard deviation and the worst value reects the algorithms robustness and the ability to against the local extremum. Standard deviation of SSABC algorithm is small except Schwefel2.26 function. Standard deviation of Sphere algorithm and Sumsquares function reaches 10-94 and 10-83 respectively. Standard deviation of Griewank function, Rastrigin function and Ackley function is zero. So SSABC algorithm can maintain the good robustness in the optimization algorithm. From average time cost, the four algorithms have the same time cost. SSABC algorithm does not increase the complexity of the algorithm and it is a more efficient algorithm for solving high-dimensional optimization question. In order to verify SSABC algorithm's advantage intuitively, we give the above eight functions' image to analysis as Figure 1(a-h).

Figure 1(a) and Figure 1(b) show that Sphere function and Sumsquares function constantly search better solution based on SSABC algorithm with the increase of iterations, and they reach to approximately 10-98 and 10-89 respectively with our new method, however, the other three methods have a bad value. Figure 1(c) presents that the results of ESABC method are closely to SSABC, but SSABC algorithm has a short convergence time and iteration. Uniquely the four algorithms have the similar results on Schwefel 2.26 function. But the result with SSABC is smaller than MABC and ABCMSS. Figure 1(e, f) obviously presents that using SSABC algorithm not only decreases the convergence time sharply, but also has the optimal function value, as well as in fig1(g,h). Other three algorithms start falling into local extremum value after 600 iterations. Figure 1(e-h), SSABC reaches optimal solution after 250 iterations and 330 iterations respectively. Thus SSABC algorithm has the superior global exploring ability and the ability to jump out of local extremum.

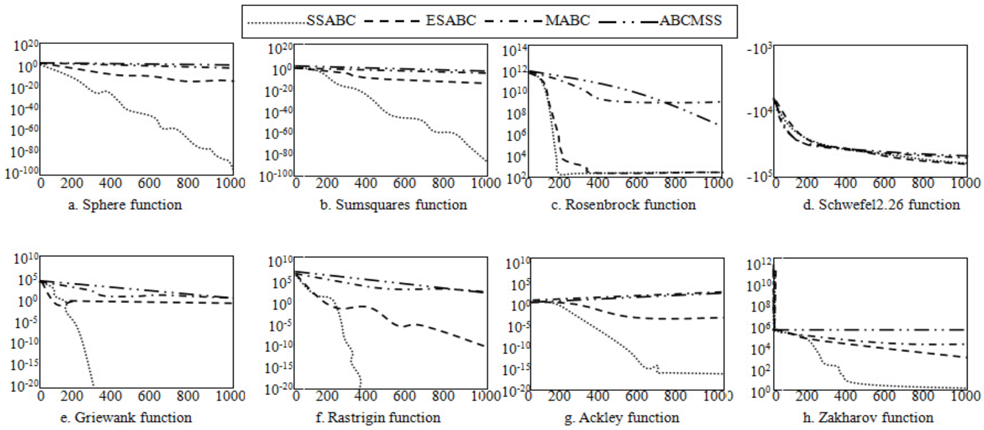


Figure 1. Function Value with four Algorithms

Table 1. Comparison of Function Optimization Results with Four Algorithms

| Function | Algorithm | Average value | Standard deviation | Optimum value | Worst value | Average time cost |
|---|---|---|---|---|---|---|
| | SSABC | $2.16e^{-95}$ | $1.401e^{-94}$ | $2.976e^{-169}$ | $9.883e^{-94}$ | 2.77412 |
| Sphere | ESABC | $6.139e^{-16}$ | $3.255e^{-15}$ | $4.621e^{-38}$ | $2.223e^{-14}$ | 2.50038 |
| | MABC | $8.995e^{1}$ | $5.346e^{1}$ | $4.069e^{0}$ | $1.978e^{2}$ | 2.34832 |
| | ABCMSS | $9.695e^{-3}$ | $1.154e^{-2}$ | $4.833e^{-4}$ | $7.376e^{-2}$ | 2.50149 |
| | SSABC | $1.917e^{-86}$ | $4.184e^{-83}$ | $2.963e^{-172}$ | $2.958e^{-77}$ | 2.77561 |
| Sumsquares | ESABC | $5.784e^{-9}$ | $2.838e^{-9}$ | $1.946e^{-31}$ | $1.901e^{-8}$ | 2.73472 |
| | MABC | $1.355e^{5}$ | $4.928e^{4}$ | $3.143e^{4}$ | $2.337e^{5}$ | 2.91828 |
| | ABCMSS | $4.284e^{4}$ | $1.475e^{4}$ | $1.763e^{5}$ | $8.472e^{4}$ | 2.65432 |
| | SSABC | $1.869e^{2}$ | $1.232e^{-1}$ | $1.983e^{2}$ | $1.989e^{2}$ | 3.01124 |
| Rosenbrock | ESABC | $1.867e^{2}$ | $1.534e^{-1}$ | $1.984e^{2}$ | $1.988e^{2}$ | 3.33189 |
| | MABC | $1.911e^{8}$ | $1.194e^{8}$ | $5.578e^{6}$ | $5.323e^{8}$ | 3.26679 |
| | ABCMSS | $3.197e^{6}$ | $2.345e^{6}$ | $3.627e^{5}$ | $1.083e^{7}$ | 3.03054 |
| | SSABC | $-7.026e^{4}$ | $9.664e^{2}$ | $-7.223e^{4}$ | $-6.806e^{4}$ | 3.10204 |
| Schwefel2.26 | ESABC | $-5.932e^{4}$ | $1.452e^{3}$ | $-6.302e^{4}$ | $-5.587e^{4}$ | 3.77659 |
| | MABC | $-5.729e^{4}$ | $1.249e^{3}$ | $-5.976e^{4}$ | $-5.485e^{4}$ | 2.90124 |
| | ABCMSS | $-5.858e^{4}$ | $1.357e^{3}$ | $-6.259e^{4}$ | $-5.586e^{4}$ | 3.33647 |
| | SSABC | 0 | 0 | 0 | 0 | 6.00122 |
| Griewank | ESABC | $4.115e^{-1}$ | $3.201e^{-1}$ | 0 | $9.767e^{-1}$ | 6.78912 |
| | MABC | $1.519e^{1}$ | $4.378e^{0}$ | $5.049e^{0}$ | $2.649e^{1}$ | 7.32321 |
| | ABCMSS | $5.435e^{0}$ | $1.519e^{0}$ | $2.576e^{0}$ | $9.976e^{1}$ | 6.67868 |
| | SSABC | 0 | 0 | 0 | 0 | 3.12121 |
| Rastrigin | ESABC | $1.157e^{-6}$ | $8.129e^{-6}$ | 0 | $5.749e^{-5}$ | 3.12513 |
| | MABC | $5.621e^{4}$ | $1.608e^{4}$ | $2.501e^{4}$ | $1.015e^{5}$ | 3.25687 |
| | ABCMSS | $1.867e^{4}$ | $6.633e^{3}$ | $6.479e^{3}$ | $3.817e^{4}$ | 2.90153 |
| | SSABC | $8.881e^{-16}$ | 0 | $8.823e^{-16}$ | $8.824e^{-16}$ | 3.98721 |
| Ackley | ESABC | $3.892e^{-4}$ | $1.983e^{-3}$ | $3.334e^{-12}$ | $1.387e^{-2}$ | 2.99234 |
| | MABC | $9.367e^{0}$ | $1.905e^{0}$ | $5.843e^{0}$ | $1.261e^{1}$ | 3.23232 |
| | ABCMSS | $2.001e^{1}$ | $7.308e^{-3}$ | $2.001e^{1}$ | $2.004e^{1}$ | 3.02364 |
| | SSABC | $2.219e^{0}$ | $2.334e^{0}$ | $8.262e^{-3}$ | $1.427e^{1}$ | 4.13864 |
| Zakharow | ESABC | $3.621e^{4}$ | $9.472e^{3}$ | $1.758e^{4}$ | $5.738e^{4}$ | 4.16758 |
| | MABC | $3.854e^{2}$ | $4.867e^{2}$ | $4.521e^{-1}$ | $2.657e^{3}$ | 3.98789 |
| | ABCMSS | $5.572e^{2}$ | $1.628e^{2}$ | $5.149e^{-1}$ | $6.102e^{3}$ | 3.62426 |

From Table 1, we can know that average value, standard deviation, optimum value, worst value and average time cost of eight functions with the four algorithms, which can illustrate the efficiency of our new algorithm. For example, average value is $2.16e^{-95}$ which is the smallest value with SSABC algorithm for Sphere function. On Sumsquares function, the standard deviation, optimum value and worst value is $4.184e^{-83}$, $2.963e^{-172}$, $2.958e^{-77}$ respectively that shows SSABC has a better optimization result. Especially, average value, standard deviation, optimum value, worst value reach to 0 with SSABC for Griewank and Rastrigin function. The last item average time cost reflects that using SSABC algorithm for the eight functions can be convergent with a fast speed and a short time. All above experiments values demonstrate that SSABC algorithm does a good job for function optimization problems.

## 4. Conclusion

This paper carries out optimization for the different stages of swarm algorithm. With the continuous evolution of algorithm, the swarm search strategies are constantly changing to meet the requirement of optimization problems. We redefine the escape behavior of the precocious individual to make it jump out of local extremum value. So we propose the improved Artificial Bee Colony in stages. The initialization of this new algorithm adopts uniform distribution and backward learning strategy which makes up the lack of a single method. It makes initial solution uniform distribute in the search space and improves the global exploring ability. We design hire bee search strategy in stage and make the hire bee has different search ability in different stage. At first stage, hire bee has strong ability of exploration and fully explores the search space, avoids algorithm fall into local extremum. At second stage, it has strong ability of production and prompts algorithm to convergent to global optimal solution quickly. Following bee search uses adaptive optimization strategy and accelerates the algorithm's convergence speed. We define the escape radius to make the escape behavior of premature individual has direction. Simulation results also prove that SSABC algorithm has the characteristics of high precision and fast convergence speed. In the future, we will make great progress on ABC algorithm based on this paper's method and apply new scheme into practical engineering application.

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