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The Journal of China Universities of Posts and Telecommunications

June 2020, 27(3): 1–20

http://jcupt.bupt.edu.cn

Research on swarm intelligence optimization algorithm

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Abstract

The bionics-based swarm intelligence optimization algorithm is a typical natural heuristic algorithm whose goal is to find the global optimal solution of the optimization problem. It simulates the group behavior of various animals and uses the information exchange and cooperation between individuals to achieve optimal goals through simple and effective interaction with experienced and intelligent individuals. This paper first introduces the principles of various swarm intelligent optimization algorithms. Then, the typical application of these swarm intelligence optimization algorithms in various fields is listed. After that, the advantages and defects of all swarm intelligence optimization algorithms are summarized. Next, the improvement strategies of various swarm intelligence optimization algorithms are explained. Finally, the future development of various swarm intelligence optimization algorithms is prospected.

Keywords bionics, natural heuristic algorithm, swarm intelligence algorithm, intelligent computing

1 Introduction

Since ancient times, the natural world is the source of all kinds of human technical thoughts, engineering principles, and major inventions. People study the structure, function and working principle of the organism, and invent new equipment, tools, and technology according to these principles, create advanced technology suitable for production, learning, and living, which is called bionics. Bionics is also considered to be a discipline closely related to cybernetics, which is mainly a discipline that compares life phenomena and mechanical principles for research and interpretation.

In recent years, the natural heuristic algorithm as an optimization algorithm has attracted extensive attention from scholars. Because of its intelligence, strong search and versatility, it is a hot topic in the research of intelligent computing. Swarm intelligence algorithms based on bionics is a typical natural heuristic algorithm. Its basic theory is to simulate the group behavior of various animals and use the information exchange and cooperation between groups to achieve the purpose of optimization through simple, limited interaction of individuals with experience and wisdom. Compared with the traditional optimization algorithm, the swarm intelligence algorithm based on bionics is essentially a probabilistic parallel search algorithm. Each individual follows simple rules that are easy to modify and expand. The individuals in the group are

Received date: 23-09-2019
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DOI: 10.19682/j.cnki.1005-8885.2020.0012

Open science identity (OSID):

opposite to each other and related to each other, showing a high degree of intelligence. Based on the above characteristics, the bionics optimization algorithm is faster without optimization and can search the global optimal solution of complex optimization problems more effectively. Common swarm intelligence algorithms include: ant colony algorithm (ACA), particle swarm optimization (PSO) algorithm, artificial fish swam (AFS) algorithm, bacterial foraging algorithm (BFA), artificial bee colony (ABC) algorithm, cat swarm optimization algorithm, firefly algorithm (FA), wolf pack algorithm (WPA), bat algorithm (BA), chicken swarm optimization algorithm, etc. The application of swarm intelligence algorithm is in traveling salesman problem, weapon target assignment problem, multiprocessor scheduling problem, reliability optimization problem, clustering problem, job scheduling problem and so on.

2 Swarm intelligence optimization algorithm

2.1 ACA

ACA was proposed by Dorigo in his doctoral thesis in 1992 [1]. It was inspired by the behavior of ants to find the path in the process of searching for food. The basic principles of ACA are as

1) Ants release pheromones in their path.

2) Ant picks a road at random when it comes to an uncrossed road. At the same time, pheromones related to path length are released.

3) Pheromone concentration is inversely proportional to path length. When the ants later encountered the junction again, they chose a path with higher pheromone concentrations.

4) Pheromone concentration on the optimal path is increasing.

5) Finally, the ant colony finds the optimal feeding path.

The process of ACA algorithm is shown in Fig. 1. In Fig. 1, t represents the current number of iterations, $G_{\max}$ is the maximum number of iterations. ACA is a kind of simulated evolutionary algorithm. This algorithm has many good qualities, such as positive feedback, distributed computing and the characteristics of the greedy heuristic search. However, ACA has disadvantages such as easy access to local optimization, too long time to search for the optimal path and slow convergence speed to find the optimal path, which is not conducive to solving optimization problems with high efficiency and high accuracy.

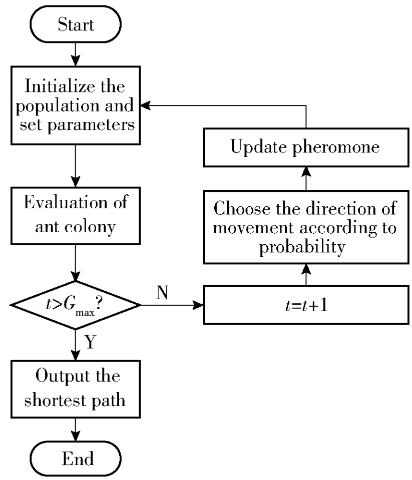

Fig. 1 The process of ACA

With the study of the theory and practical application of ACA, its applications include vehicle routing problem (VRP) [2–4], production scheduling problem (PSP) [5–6], robot path planning [7], network routing [8], biology and medicine [9–10], image processing [11–12], clustering [13] and so on.

2.2 PSO algorithm

PSO algorithm is an effective bionic optimization algorithm, which was proposed by Kennedy et al. in 1995 [14].

PSO algorithm adopts the speed-position search model, and its basic idea is as follows: let the number of target search space be D, and a group is composed of N particles, where the ith particle can be represented by the D-dimensional vector $\boldsymbol{X}_i = (x_{i1}, x_{i2}, \dots, x_{iD})$, $i = 1, 2, \dots, N$. The position of each particle is a potential solution. If $\boldsymbol{X}_i$ is substituted into the objective function, its fitness value can be obtained, and the value of the fitness can be used to evaluate the merits of the solution. The flight velocity of the ith particle $\boldsymbol{V}_i = (v_{i1}, v_{i2}, \dots, v_{iD})$ and the current optimal position $\boldsymbol{p}_g = (p_{g1}, p_{g2}, \dots, p_{gD})$, then the updated formula of particle velocity and position is

$$v_{id}^{k+1} = v_{id}^{k} + C_1 \mathrm{rand}_1^k (p_{id}^k - x_{id}^k) + C_2 \mathrm{rand}_2^k (p_{gd}^k - x_{id}^k) \tag{1}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{2}$$

where the learning factors C_1 and C_2 are non-negative. $\mathrm{rand}_1^k(\cdot)$ and $\mathrm{rand}_2^k(\cdot)$ are uniformly distributed and mutually independent pseudo-random numbers on the interval [0, 1]. The speed upper limit is constant $|v_{id}| \leqslant v_{\max id}$. The process of PSO algorithm is shown in Fig. 2.

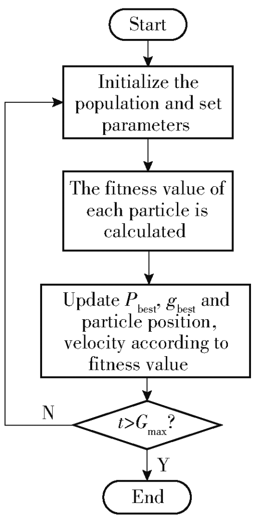

Fig. 2 The process of PSO algorithm

In Fig. 2, P_{best} is the optimal position for individuals. g_{best} is the global optimal position. PSO algorithm is an iterative optimization algorithm. The classical PSO algorithm is simple in calculation, fast in convergence, and has few parameters, but it is easy to fall into local minimum points, low in searching and sending accuracy, and poor in processing effect for discrete problems. PSO algorithm was widely used in the genetic algorithm (GA) [15], neural network training [16 - 17], fuzzy system control [18 - 19] and so on.

2.3 AFS algorithm

Based on the theory of artificial fish, Li et al. proposed a new swarm intelligence optimization algorithm based on animal behavior—AFS in 2002 [20], which was inspired by the foraging, clustering and rear-ending behaviors of fish.

The process of the AFS is as follows:

Step 1 Foraging behavior. The current state of the artificial fish is represented by $\boldsymbol{X}_i$, and state $\boldsymbol{X}_j$ is randomly selected within other visible domains ($d_{i,j} \leqslant S_{\mathrm{visual}}$). S_{visual} represents the scope of the visible domain. If the food concentration (FC) V_{FC} in the current state is less than the FC V_{FC} in state $\boldsymbol{X}_j$, it will move forward in the direction of state $\boldsymbol{X}_j$. Otherwise, it needs to select state $\boldsymbol{X}_j$ in other visible domains again. After repeated execution for several times, the condition of even advance is still not satisfied, so it moves one step by itself. The above process can be described as

$$x_{i\mathrm{next}k} = \begin{cases} x_{ik} + \dfrac{\mathrm{rand}(S_{\max})(x_{ij} - x_{ik})}{\| \boldsymbol{X}_j - \boldsymbol{X}_i \|}; & V_{\mathrm{FC}_j} > V_{\mathrm{FC}_i} \\ x_{ik} + \mathrm{rand}(S_{\max}); & V_{\mathrm{FC}_j} \leqslant V_{\mathrm{FC}_i} \end{cases} \tag{3}$$

where x_{jk}, x_{ik}, $x_{i\mathrm{next}k}$ are respectively the state vector $\boldsymbol{X}_j$, $\boldsymbol{X}_i$ and the next state vector $\boldsymbol{X}_{i\mathrm{next}}$ of the artificial fish, and $\mathrm{rand}(S_{\max})$ is the random number between $[0, S_{\max}]$.

Step 2 Clustering behavior. n represents the number of partners in the visible domain of artificial fish, forming the set S_{KJ}.

$$S_{\mathrm{KJ}_i} = \{\boldsymbol{X}_j \mid \| \boldsymbol{X}_j - \boldsymbol{X}_i \| \leqslant V\} \tag{4}$$

If $S_{\mathrm{KJ}_i} = \varnothing$ ($\varnothing$ is an empty set), indicates that no other partner is in its visible field, $n < 1$. Otherwise, n is greater than or equal to 1. Calculate the partner's central position $\boldsymbol{X}$.

$$x_{\mathrm{c}k} = \frac{1}{n} \sum_{j=1}^{n} x_{jk} \tag{5}$$

where x_{jk} represents the kth element of the jth partner $\boldsymbol{X}_j$, $j = 1, 2, \ldots, N$. $x_{\mathrm{c}k}$ represents the kth element of the central position state vector $\boldsymbol{X}_{\mathrm{c}}$. A_q is the safety factor. Then calculate the FC V_{FC_i} at the center. If satisfied

$$\mathrm{e}^{A_q} \frac{V_{\mathrm{FC}_i}}{\delta} > V_{\mathrm{FC}_i}; \quad A_q \leqslant 1, \ \delta > 1 \tag{6}$$

Eq. (6) indicates that the central location of partners is not too crowded and the security is high, then Eq. (7) can be calculated. Otherwise, perform foraging behavior.

$$x_{i\mathrm{next}k} = \frac{x_{ik} + \mathrm{rand}(S_{\max})(x_{\mathrm{c}k} - x_{ik})}{\| \boldsymbol{X}_{\mathrm{c}} - \boldsymbol{X}_i \|} \tag{7}$$

If $S_{\mathrm{KJ}_i} = \varnothing$, indicates that no other partner is in its visible field, so perform foraging behavior in Step 1.

Step 3 Rear-end behavior. In the visible domain of the artificial fish, search partner $\boldsymbol{X}_{\max}$ with the largest FC to satisfy the requirement

$$x_{i\text{next}k}=\frac{x_{ik}+\text{rand}(S_{\max})(x_{\max k}-x_{ik})}{\|\boldsymbol{X}_{\max}-\boldsymbol{X}_i\|} \tag{8}$$

where $x_{\max k}$ represents the kth element of state vector $\boldsymbol{X}_{\max}$. If there is no other partner in the current visible domain, the foraging behavior in Step 1 can be carried out. A bulletin board is set up in the AFS to record the FC value and its state of the optimal artificial fish. Each artificial fish will compare its current state with the bulletin board after one movement is completed. When its state is better than the state on the bulletin board, it will replace the state on the bulletin board with its state.

AFS has the following characteristics, strong ability to jump out of the local optimal solution, fast convergence speed, and parallel processing can be implemented, but the obtained feasible solution is not high precision. Its main applications include clustering [21], multi-objective optimization [22], biology and medicine [23 – 24], production and scheduling [25] and so on.

2.4 BFA

BFA is proposed by Passino in 2002 based on the bacterial behavior of E-coli bacteria in the human intestinal tract [26]. In the model based on BFA, the solution of the optimization problem corresponds to the state of bacteria in the search space, namely the fitness value of the optimization function. BFA consists of five behaviors: chemotaxis, swarming, reproduction, elimination, and dispersal.

Initialization parameters. Include population size S, spatial dimension P, the number of chemotactic behavior N_c, the maximum number of steps forward for chemotactic operation N_s, replicative operation N_{re}, the number of migration operation N_{ed}, migration probability P_{ed}, the information contained in bacteria i is expressed as a D vector, $\boldsymbol{\theta}^i=[\theta^{i1},\theta^{i2},\ldots,\theta^{iD}]$, $i=1,2,\ldots,N$, the tropism step $C(i)$. The process of BFA is shown in Fig. 3.

BFA is simple and easy to implement, with strong parallel processing ability and global searchability, but it also has disadvantages such as the influence of parameters on the overall performance and slow convergence speed. Its main applications include power system [27], image processing [28], neural network [29], clustering [30], filter design [31], pattern recognition [32], production, scheduling [33] and so on.

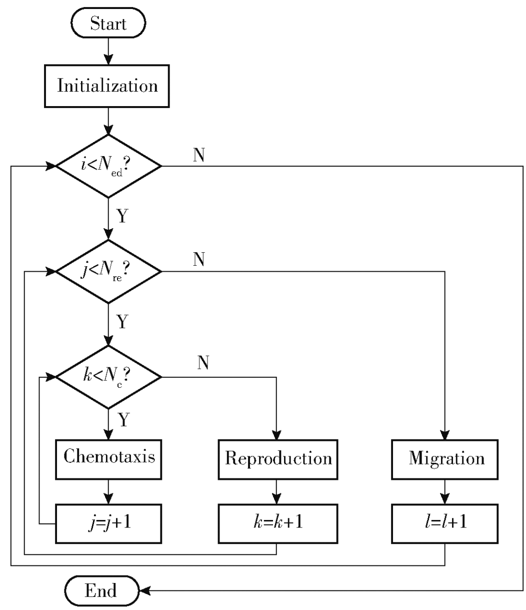

Fig. 3 The process of BFA

2.5 ABC algorithm

To better solve the function optimization problem, Yang et al. [34] simulated the honeybee's honey collecting behavior and proposed a new bionic intelligent optimization algorithm: ABC algorithm in 2005.

The process of the ABC is as follows:

Step 1 Initialize each honey source $\boldsymbol{X}_i$, set parameters N_P, limit and the maximum number of iterations, set $T=1$.

Step 2 Assign a leader bee to honey source $\boldsymbol{X}_i$ and search according to Eq. (9) to generate new honey source v_i.

$$v_{id}=x_{id}+\varphi(x_{id}-x_{jd}) \tag{9}$$

where d is a random integer in $\{1, 2, \ldots, d\}$, indicating that the lead bee randomly selects one dimension for search. $j\in\{1,2,\ldots,N_P\}, j\neq i$, it means that a honey source which is not equal to i is randomly selected from N_P honey sources. $\varphi(\cdot)$ is a random number uniformly distributed in [−1, 1].

Step 3 Evaluate the fitness value of v_i according to Eq. (10), and determine the preserved honey source according to the greedy selection method.

$$V_{\mathrm{fit}_i} = \begin{cases} \dfrac{1}{1+f_i}; & f_i \geqslant 0 \\ 1+|f_i|; & f_i<0 \end{cases} \tag{10}$$

where f_i represents the function value of the solution.

Step 4 According to Eq. (11) calculates the probability that the honey source found by the leading bees will be followed

$$p_i = \frac{V_{\mathrm{fit}}}{\sum_{i=1}^{N_{\mathrm{P}}} V_{\mathrm{fit}_i}} \tag{11}$$

Step 5 Follow the peak to search in the same way as the leader bee, and determine the retained honey source according to the greedy selection method.

Step 6 Judge whether honey source $\boldsymbol{X}_i$ meets the condition of being abandoned. If satisfied, the corresponding leading bee role becomes the scout bee, otherwise, it is directly transferred to Step 8.

Step 7 According to Eq. (12), scout bees randomly generate new honey sources.

$$\boldsymbol{X}_i^{t+1} = \begin{cases} \boldsymbol{L}_d + (\boldsymbol{U}_d - \boldsymbol{L}_d)\,\mathrm{rand}(0,1); & V_{\mathrm{trial}_i} \geqslant V_{\mathrm{limit}} \\ \boldsymbol{X}_i^t; & V_{\mathrm{trial}_i} < V_{\mathrm{limit}} \end{cases} \tag{12}$$

Step 8 $t = t+1$. Determine whether the algorithm meets the termination condition. If satisfied, terminate and output the optimal solution. Otherwise, return to Step 2.

ABC has the characteristics of simple operation, fewer control parameters, higher search precision, and stronger robustness. Compared with GA, differential evolutionary (DE) algorithm and PSO, ABC has better solution quality. At present, ABC was successfully applied in neural network training [35], clustering [36], constrained optimization problem [37], multi-objective optimization [38], power system optimization [39], system and engineering design [40], image processing [41], network service [42] and so on.

2.6 Cat swarm optimization algorithm

Cat swarm optimization algorithm is a global optimization algorithm based on cat behavior first proposed by Chu et al. in 2006 [43]. Cat swarm optimization algorithm divides the behavior of cats into two patterns, one is the pattern when the cat is lazy and looks around, which is called the searching pattern, and the other is the pattern when tracking the dynamic target, which is called the tracing pattern. The two modes interact by combining mixture ratio (MR), which represents the proportion of the number of cats in the tracking mode in the entire cat population. The process of cat swarm optimization algorithm is shown in Fig. 4.

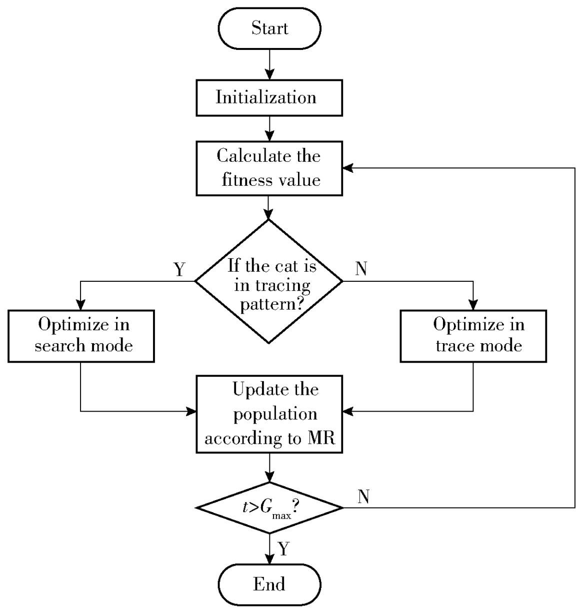

Fig. 4 The process of cat swarm optimizaton algorithm

The main application fields of cat swarm optimizaton algorithm include group multi-objective optimization [44], clustering [45], filter [46], production and scheduling [47], cloud computing [48] and so on.

2.7 FA

Yang proposed the FA in 2008 based on the luminescence characteristics and mutual attraction behavior of individual fireflies [49].

The key idea of FA is that the firefly with low brightness is attracted to the firefly with high brightness and moves towards it and updates its position. The brightness of the firefly depends on the target value of its position. The higher the brightness, the better the target value, and the stronger the ability to attract other fireflies. Fireflies move randomly if neighboring individuals are equally bright. The process of FA is shown in Fig. 5.

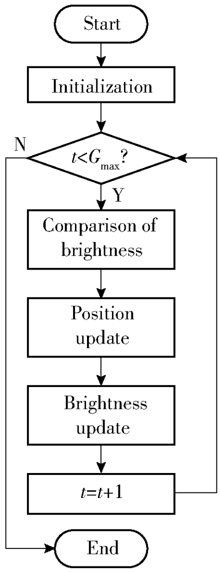

Fig. 5 The process of FA

FA is a population intelligent heuristic optimization algorithm with the advantages of simple concepts, few parameters to be adjusted, easy application and implementation. The main application fields of firefly algorithm include the power system [50], clustering [51], image processing [52], PID control [53], neural network [54] and so on.

2.8 BA

BA was proposed by Yang in 2010 [55], inspired by the echolocation behavior of bats when they forage for food. BA simulates the prey-hunting behavior of bats by echolocation to find the optimal solution to the problem. Every bat individuals as current within the feasible region of a solution, each solution corresponding to an optimization problem to determine the fitness value, per bat by adjusting the pulse wavelength, volume, pulse emissivity of three parameters to follow the current optimal bats, make the whole population in solution space from disorderly to orderly to deepen, so as to obtain the optimal solution.

The rules of BA are as follows:

1) All bats use echolocation to sense distance, and they can know the difference between food/prey and a background obstacle in a way.

2) The bat is flying at position $\boldsymbol{X}_i$ with velocity $\boldsymbol{V}_i$, searching for prey with fixed frequency $f_{\min}$, variable wavelength λ, and loudness A_0. They can automatically adjust the emitted pulse wavelength (or frequency) according to the distance between the target and themselves, and adjust the frequency of the emitted pulse $r \in [0,1]$ when approaching the prey.

3) Although loudness varies in many ways, this paper assumes it varies from a maximum (positive) A_0 to a fixed minimum $A_{\min}$.

The process of BA is as follows:

Step 1 Initialization. Let m bats form a bat colony, and the position of the ith bat is $\boldsymbol{X}_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, $i = 1, 2, \ldots, N$, velocity is $\boldsymbol{V}_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$. The pulse frequency of the sound wave emitted by the random initial bat at $\boldsymbol{X}_i$ is f_i. The loudness A_0 is the pulse, the pulse transmission rate is r_i, the maximum frequency is $Q_{\max}$ and the minimum frequency is $Q_{\min}$.

Step 2 Calculate the optimal position P_{gd} of bats in the colony.

Step 3 Update the position $\boldsymbol{X}_i$ and speed $\boldsymbol{V}_i$ of the ith bat according to Eqs. (13) – (15) and check whether the $\boldsymbol{X}_i$ is out of bounds.

$$f_i = f_{\min} + (f_{\max} - f_{\min})\mathrm{rand}(0,\ 1) \tag{13}$$

$$\boldsymbol{V}_i^t = \boldsymbol{V}_i^{t-1} + (\boldsymbol{X}_i^{t-1} - \boldsymbol{X}_*) f_i \tag{14}$$

$$\boldsymbol{X}_i^t = \boldsymbol{X}_i^{t-1} + \boldsymbol{V}_i^t \tag{15}$$

where $\boldsymbol{X}_*$ is the current global optimal position.

Step 4 To determine whether rand(0,1) is greater than r_i, if not, perform Step 6, if it is, it will turn to local search, randomly select a solution from the best solution, and generate a new local solution near the solution according to Eq. (16).

$$\boldsymbol{X}_{\mathrm{new}} = \boldsymbol{X}_{\mathrm{old}} + \mathrm{rand}(0,1)\boldsymbol{A}^t \tag{16}$$

Step 5 Fitness comparison. If the fitness of the new solution is better than that of the current solution and rand( ) $< A$, update the position of the bat.

Step 6 Global fitness comparison. If the fitness of bat i is better than P_{gd} in the current iteration, then replace P_{gd} with $\boldsymbol{X}_i$, otherwise, P_{gd} remains unchanged.

Step 7 Loudness A_i and pulse rate r_i are updated by Eqs. (17) and (18).

$$A_i^{t+1} = \alpha A_i^t \tag{17}$$

$$r_i^{t+1} = r_i^0 (1 - e^{-\gamma t}) \tag{18}$$

Step 8 To determine whether the loop reaches the maximum iteration number. If so, stop and output the global optimal solution P_{gd}. Otherwise, return to Step 3.

Due to BA of simple structure, few parameters, strong robustness, easy to understand, and many scholars have applied it to optimization problems, include function optimization [56], image processing [57], production scheduling [58], artificial intelligence [59], power system [60] and so on.

2.9 WPA

WPA was first proposed by Yang et al. [61], and a new wolf colony algorithm (WCA) was proposed by Liu et al. [62] in 2011 to solve the optimization problem. WCA simulates the hunting behavior of wolves in nature and abstracts the search behavior, siege behavior, and update behavior.

The process of WPA is as follows:

Step 1 Initialization. Suppose that the dimension of the searching space is D, and the number of the individual member is n, the position of the ith wolf is $\boldsymbol{X}_i = (x_{i1}, x_{i2}, ..., x_{iD})$.

Step 2 Searching behavior. Each searching wolf goes further in the direction of h in step $\boldsymbol{a}$, calculate the concentration of the prey perceived in each direction, and select the strongest concentration as the optimal position. Then the position of the ith researching wolf to the $P = [1, 2, ..., N]$ direction is updated, then

$$\boldsymbol{X}_j = \boldsymbol{X}_i + \boldsymbol{a}\,\mathrm{rand}(-1, 1) \tag{19}$$

where $\boldsymbol{a}$ is the searching step, the maximum searching number is $N_{\max}$. If the searching number is larger than $N_{\max}$ or the current position is better than the optimal searching position, the searching behavior ends.

Step 3 Besiege the quarry. When a searching wolf finds prey, it calls upon its companion to howl and besiege it. For the wolves of generation k, G_d^k is the position of prey in the D dimensional space, so the siege behavior of the prey by the wolves can be expressed as

$$x_{id}^{k+1} = x_{id}^k + b(G_d^k - x_{id}^k)\,\mathrm{rand}(-1, 1) \tag{20}$$

where b is the besieging step, k is the iteration number, the range of the dth position is $[x_{\mathrm{min}d}, x_{\mathrm{max}d}]$. If the value calculated by Eq. (20) exceeds the range, set it as the boundary value.

Step 4 Update. According to the principle of strong survival, the wolf pack is updated, and m new wolves are randomly produced to replace the m wolves with the smallest objective function.

Step 5 Determine whether the maximum iteration number is reached. If so, stop and output the optimal position of the artificial wolf. Otherwise, return to Step 2.

Compared with PSO and GA, WPA has fewer sensitive parameters, strong robustness, fast convergence speed, and high accuracy. WPA was applied in path planning [63], image processing [64], production and scheduling [65], power system [66], artificial intelligence [67] and so on.

2.10 Chicken swarm optimization algorithm

Chicken swarm optimization algorithm is an intelligent search algorithm based on chicken swarm foraging behavior proposed by Meng et al. [68] in 2014, which transforms the chicken swarm search behavior and hierarchy into the optimization problem of seeking the best value in a fixed area. The rules of chicken swarm optimization algorithm are as follows:

1) The chicken swarm is divided into several subgroups, each group is composed of a rooster, a small number of hens and more chickens.

2) According to the different fitness value to distribute the population of the rooster, hen, and chicken.

3) The system of superior and subordinate in the swarm is redistributed after reaching a certain generation.

4) The chicken swarm forages according to the hierarchy, and the chicks can feed on the food found by other individuals.

The process of chicken swarm optimization algorithm is as follows:

Step 1 Initialization. Initialize a swarm of chickens, including the total number of individuals N, the number of roosters N_R, hens N_H, chicks N_c and hens with offspring N_M. Determine the maximum number of iterations of the swarm T, the number of subgroup G.

Step 2 Calculate the fitness value of the chicken swarm and initialize the individual optimization position p_{best} and the current iteration number g_{best}.

Step 3 Establish a hierarchy. Each individual was ranked according to fitness value, and a hierarchy was established according to the ranking results. The corresponding relationship between hens and chickens was randomly assigned.

Step 4 Update position. According to the position updating Eqs. (21) and (22), the positions of the rooster, hen, and chick are updated respectively. The updated formula of rooster's position is

$$X_{i,j}(t+1) = X_{i,j}(t)(1+\mathscr{C}(0,\sigma^2)) \tag{21}$$

$$\sigma^2 = \begin{cases} 1; & f_i \leqslant f_w \\ e^{\frac{f_w - f_i}{|f_i| + \beta}}; & f_i > f_w \end{cases} \tag{22}$$

where $\mathscr{C}(0, \sigma^2)$ is a Gaussian distribution with mean 0 and standard deviation σ^2. The updated formula for the hen's position is

$$X_{i,j}(t+1) = X_{i,j}(t) + S_1 \mathrm{rand}(0,1)(X^t_{r_1,j} - X^t_{i,j}) + S_2 \mathrm{rand}(0,1)(X^t_{r_2,j} - X^t_{i,j}) \tag{23}$$

$$S_1 = e^{\frac{f_i - f_{r1}}{|f_i| + \varepsilon}} \tag{24}$$

$$S_2 = e^{f_{r2} - f_i} \tag{25}$$

where r_1 is an index of the rooster, which is the ith hen's group-mate. r_2 is an index of the chicken (rooster or hen), which is randomly chosen from the swarm. The updated formula for the chick's position is

$$X_{i,j}(t+1) = X_{i,j}(t) + V_{FL}(X^t_{m,j} - X^t_{i,j}) \tag{26}$$

where $X^t_{m,j}$ represents the position of the mth hen in the jth dimension at the tth iteration. V_{FL} is a parameter, which means the chick would follow its mother to forage for food.

Step 5 Update fitness value. The fitness value of the individual after the position update is calculated, and the fitness value is compared with the last fitness value. If the fitness value is better, it will be updated. Otherwise, it remains unchanged.

Step 6 Update the iteration number of the population. Determine whether the maximum iteration number is reached. If so, stop. Otherwise, perform Step 2.

Chicken swarm optimization algorithm has the advantages of fast convergence speed and high convergence efficiency, but the solution precision is low and the local search is weak. The main application fields of chicken swarm optimization algorithm are image processing [69], sensor and communication [70], production and scheduling [71], power system [72] and so on.

2.11 Comparison of various swarm intelligence optimization algorithm

To sum up, the paper compares the advantages and defects of various algorithms, their application scopes, and the results are shown in Table 1. The comparison of other basic parameters of swarm intelligence optimization algorithms is shown in Table 2.

Table 1 Comparison of various swarm intelligence optimization algorithm

Algorithm	Advantage	Defect
ACA	Strong robustness, high search accuracy and easy to be combined with other algorithm	Easy to enter the local optimum, the time of searching the optimal path is too long, and the convergence speed of searching the optimal path is slow
PSO	Simple calculation, fast convergence and few parameters	Easy to fall into local minimum points, search accuracy is not high, the processing of discrete problems is not good
AFS	Easy to implement and insensitive to the initial value and parameter selection. Strong ability to jump out of local optimal solution, fast convergence and parallel processing	The search speed is slow, and the solution accuracy is not high

Table 1 continued

Algorithm	Advantage	Defect
BFA	Strong parallel processing capability and global search capability. It is not easy to get into the local minimum and has strong robustness	Chemotaxis with fixed step size and migration with fixed probability make it easy to lose excellent individuals in the later stage, affecting the speed and quality of optimization
ABC	Simple operation, fewer control parameters, high search precision, and strong robustness	It has the defect of premature convergence, weak local search ability and slow convergence speed
Cat swarm optimization algorithm	Easy to implement and converges quickly	Easy to fall into premature, slow running speed
FA	Simple model, fast computation, few parameters, and easy to be applied and implemented	The parameters in standard FA are set in advance, which will lead to premature convergence of the algorithm, or the algorithm cannot converge due to improper parameter setting. Convergence speed is slow. Easy to fall into the local minimum point
BA	Model is simple and the parameters are few, the convergence speed is fast, good robustness	Premature convergence and low convergence accuracy
WPA	Convergence speed is fast, it has strong global and local searching ability, high population diversity and strong robustness	With more parameters, longer operation time and more complex algorithm, easy to fall into local optimization
Chicken swarm optimization algorithm	Fast convergence speed, high convergence accuracy, good optimization effect, and strong robustness	For high latitude optimization problems, the convergence accuracy is low and premature convergence

Table 2 Comparison of other basic parameters of swarm intelligence optimization algorithm

Algorithm	Rate of convergence	Accuracy of solution	Algorithm complexity	Adjustable parameters	Sensitive to initial values
ACA	Slow	High	Low	Few	Yes
PSO	Fast	Low	Low	Few	Yes
AFS	Faster then slower	Low	Low	Many	Yes
BFA	Slow	High	Low	Many	No
ABC	Fast	Low	Low	Few	No
Cat swarm optimization algorithm	Slow	Low	Low	Few	No
FA	Faster then slower	Low	Low	Few	Yes
BA	Fast	Low	High	Many	No
WPA	Fast	Low	Low	Few	No
Chicken swarm optimization algorithm	Fast	Low	Low	Few	No

3 Improvement strategy and prospect of swarm intelligence optimization algorithm

3.1 ACA

3.1.1 Improvement strategy of ACA

ACA was proposed more than 20 years, domestic and foreign scholars proposed many effective improved algorithms from the aspects of the improved pheromone adjustment mechanism, search strategy, and integration with other bionic optimization algorithms, aiming at the disadvantages of slow convergence and easy stagnation of standard ACA.

1) The fusion of ACA

Shelokar et al. [73] proposed the PSACO algorithm, it is a continuous optimization scheme that combined ant colony optimization (ACO) and PSO, and the whole process was divided into two stages. In the first phase, ACO was used, and in the second phase, PSO was used. ACO works as a local search, wherein, ants apply the pheromone-guided mechanism to refine the positions found by particles in the PSO stage. In PSACO, a simple pheromone-guided mechanism of ACO is proposed to apply as the local search. Some scholars combine AFS with ACA [74].

2) The pheromone improvement strategy

Dorigo et al. [75] proposed the modified ACA using update local pheromone strategy, which can improve the probability of unvisited path selection and enhance the global search ability of the algorithm. The spatial global pheromone updating strategy is applied to strengthen the concentration of pheromones obtained on the localily optimal path so that the positive feedback effect of the algorithm can be enhanced and the convergence speed of the algorithm can be accelerated.

3) Improved path selection strategy

Reasonable path selection strategy of improved ACA in the process of optimization is conducive to reducing the possibility that ACA is prone to fall into local optimum and improving the performance of the algorithm. Modified ACA [75] uses an improved routing strategy to guide the optimization of the initial phase of ants, able to quickly find an acceptable efficient solution and the current state of information accumulation system. The algorithm can effectively improve the convergence speed and it has a certain random operation, which can improve the performance of ACA.

3.1.2 Prospect of ACA

The selection of key parameters and the setting of initial values in the algorithm are empirical to some extent and lack of scientific theoretical demonstration. The application in different optimization fields is mostly based on the simulation experiment of the problem. Therefore, future research can be carried out in the following aspects:

1) Based on the existing research results, it is need to further understand the correlation between the algorithm parameters and its influence on the algorithm solution performance, and continue to dig other behaviors of the ant colony.

2) The development of intelligent integration with other emerging bionic algorithms (such as FA, mixed leapfrog algorithm, etc.) will improve and enrich the theory and application of ant colony algorithm.

3.2 Improvement strategy and proposect of PSO algorithm

3.2.1 Improvement strategy of PSO

PSO algorithm has the following disadvantages. The optimal solution found maybe the local optimal solution rather than the global optimal solution. The convergence speed of the algorithm is fast at the initial stage of search and slow at the later stage. Randomness of parameter selection. Because of these defects, researchers have made different improvements to the PSO to compensate for these shortcomings.

1) Add compression factor

Clerc et al. [76] introduced the compression factor into the PSO and improved the speed update method of the algorithm. The introduction of the compression factor can control the convergence of the PSO so that the particles have the opportunity to search for different regions in the space and obtain high-quality particles. This method greatly improves the convergence speed and accuracy of PSO.

2) Collaborative PSO

Van den Bergh et al. [77] proposed a collaborative PSO algorithm. The specific steps of this method are as follows. The dimension of the particle is n, the whole particle is divided into small parts, and then the algorithm optimizes each small part (one dimension) of the particle, evaluates the fitness value and merges it into a complete particle. The algorithm has faster convergence speed on many problems and good results are obtained.

3) Hybrid algorithm

Angeline [78] introduced the natural selection mechanism into the PSO to form a new PSO algorithm based on natural selection. The key idea is that after the algorithm updates all the particles, the fitness value of the particles is calculated and the fitness value of the particles is sorted. Then, according to the sorting results, the best half of the particles in the particle population is replaced by the worst half of the particles in the particle population, but the optimal position information of the original particles is retained. The introduction of the natural selection mechanism enhanced the global optimization ability of particles and improved the accuracy of the algorithm.

3.2.2 Prospect of PSO

The performance of PSO was significantly improved by different methods, but the theoretical basis and analysis of PSO are still weak. Therefore, strengthening the theoretical analysis of PSO is an important research direction in the future. Future research can be carried out in the following aspects:

1) Aiming at the disadvantages of PSO, such as easily falling into local optimum and poor convergence, a better improvement strategy is sought to improve its performance.

2) Because of PSO's simple structure and easy implementation, PSO is also a hot topic in more practical problems.

3.3 Improvement strategy and prospect of AFS algorithm

3.3.1 Improvement strategy of AFS

Relevant researches show that the AFS has a fast convergence rate in the early stage but tends to gather near the local optimal point in the later stage, and the solution accuracy is low. Therefore, many scholars have carried out relevant researches and improvement. The main improvement is divided into two aspects. The parameters are self-adjusted and integrated with other swarm intelligence algorithms to increase the diversity of the swarm.

1) Parameter adjustment

In Ref. [79], another method is adopted to realize adaptive parameter adjustment, so that the parameters such as step length, visual field, and congestion factor are automatically adjusted with the calculation, so as to ensure that the algorithm can conduct fine local search in the later stage and improve the algorithm's solution accuracy. In the paper, the rate of change and variance of the adaptive value were used to determine whether to adjust the parameters, which improved the search scope and solution accuracy.

2) Hybrid algorithm

Jiang et al. [80] presented a hybrid algorithm based on PSO and AFS. It combined the advantages of PSO and AFS. An improved AFS was introduced during the iteration. The algorithm performed the following behaviors and clustering behaviors simultaneously on two subgroups. It increased the diversity of the swarm and improved the accuracy of the solution.

3.3.2 Prospect of AFS

AFS algorithm was born in a short time, and lots of researches focus on the improvement and application. The theoretical study of this algorithm is less involved. Therefore, future research can be conducted from the following aspects.

1) The following research should imitate the research of GA, the research should be conducted on its evolutionary drift mode, population variation mechanism and solving ability of algorithm under noise environment.

2) Further, improve the algorithm and expand the application field of the algorithm.

3.4 Improvement strategy and prospect of BFA

3.4.1 Improvement strategy of BFA

BFA has the advantages of swarm intelligence algorithm parallel search and easy to jump out of the local minimum. The improvement strategy of BFA mainly includes the following three aspects:

1) Improved algorithm rules and parameter

Datta et al. [81] proposed an improved adaptive algorithm, which made use of the adaptive delta modulation principle to make BFA has adaptive characteristics, and this algorithm could improve the convergence speed and accuracy of the algorithm. Biswas, et al. [82] studied the influence of replication operation on the convergence performance and stability of the algorithm.

2) Dynamic multi-population cooperative operation

Chatzis et al. [83] proposed the bacterial foraging optimization (BFO)-based collaborative microbial community optimization algorithm (SBSO). The new algorithm included two improvements. One is introducing the population dynamics of PSO in BFO environment to improve the convergence of the foraging mechanism of BFO bacteria, the other is different components of solution vectors of multiple populations are utilized for collaborative optimization to alleviate the dimensionality problem of the algorithm. The accuracy of the algorithm is improved.

3) Hybrid algorithm

Bakwad, et al. [84] proposed the bacterial foraging fusion algorithm based on parameter-free PSO (HBF-PFPSO). This algorithm improved the quality of global optimization of multimodal functions. There are two rules in BFO are modified. This algorithm not only converged quickly but also obtained a better optimal solution.

3.4.2 Prospect of BFA

BFA was proposed more than ten years. The algorithm was constantly studied and improved, and there was still a lot of room for development in its mathematical model and theoretical research. The algorithm can be studied in the following aspects of the future.

1) Due to the parameter selection algorithm is mainly gained by many experiments, the lack of general adaptive method, and try to use some traditional mathematical laws to achieve parameter adaptive setting, at the same time, the stand or fall of parameters on the algorithm optimization results play a decisive role, the selection of parameters is of great significance.

2) Compared with similar intelligent algorithms, the theoretical research of BFA is not perfect. For the problems of convergence analysis, it is mostly verified by standard test functions, leading to specific problems that cannot be analyzed in detail. Therefore, the research on the superior performance of the algorithm is of vital importance.

3) At present, many mechanisms of the intelligent algorithm can be fused with BFA, such as clonal selection algorithm, cultural algorithm, fish swarm algorithm and so on. The emergence of their advantages to give full play to the performance of the algorithm, fusion technology is a very important topic in the future intelligent algorithm research.

4) When BFA is specifically applied to solve practical problems, the excellent improved algorithm based on different test functions can provide references for solving the classification of practical problems. Therefore, it is of certain significance to expand the application of the algorithm in the field of life and engineering applications.

3.5 Improvement strategy and prospect of ABC algorithm

3.5.1 Improvement strategy of ABC algorithm

ABC algorithm has the following problems. One is the algorithm has premature convergence, the other is algorithm has good exploration ability, but insufficient development ability, weak local searchability, and relatively slow convergence speed. Because of the shortcomings of the ABC algorithm, domestic and foreign scholars put forward many improved schemes, and the research results are simply summarized into three aspects. Algorithm parameter adjustment, hybrid algorithm, and design a new learning strategy.

1) Parameter adjustment

Akay et al. [85] studied the influence of parameter setting on the performance of ABC algorithm through multiple experimental systems and the following conclusions are given. Colony size (CZ) has no obvious influence on the performance of the ABC algorithm, and a satisfactory solution can be obtained even if the CZ is small. Limit value has great influence on the performance of the algorithm, too small limit is not conducive to swarm cooperative search, too large limit reduces the ability of the algorithm to explore. For more complex functions, a limit set to $V_{CZ}D$ is a better initial choice. D is the cycle number.

2) Hybrid algorithm

Elabd [86] proposed a hybrid algorithm using the ABC algorithm to improve the optimal position of individual particles in the PSO algorithm. When being applied to high-dimensional optimization problems, the PSO algorithm may be trapped in the local optimal because of its low global exploration efficiency. ABC algorithm has slower convergence speed in some cases because of the lack of powerful local exploitation capacity. So, Li et al. proposed a hybrid algorithm called particle swarm and artificial bee colony algorithm (PS-ABC) [87], which combined the local search phase in PSO with two global search phases in ABC for the global optimum. In the iteration process, the algorithm examined the aging degree of P_{best} (the current optimal position) for each individual to decide which type of search phase (PSO algorithm phase, onlooker bee phase, and modified scout bee phase) to be adopted. The PS-ABC algorithm is an efficient, fast converging and robust optimization algorithm for solving high-dimensional optimization problems.

3) New learning strategy

Banharnsakun et al. [88] added the fitness value of the best individual (best-so-far) to the following bee search formula to improve the development ability, and the search radius decreased linearly with the increase of the number of iterations. The experimental results of the standard test function and the application in image compression showed that this algorithm can quickly find high-quality solutions.

3.5.2 Prospect of ABC algorithm

Review the research status of the ABC algorithm, generally speaking, its related research is still poor, and there are many problems worth further study, so future research can be carried out from the following aspects.

1) Theoretical research

Similar to other intelligent optimization algorithms, ABC algorithm lacks theoretical research, so it is theoretically unable to analyze the behavior of the algorithm. Since the establishment of the convergence model and the analysis of convergence are the basis of algorithm research and improvement, the work in this aspect is challenging.

2) Adaptive strategy of parameters

Reasonable parameter setting is very important to the performance of the algorithm. In a general sense, the setting of parameters has a problem dependency. Therefore, according to the characteristics of the problem and the search process, it is of great significance to design the adaptive change mechanism of parameters to improve the performance of the algorithm.

3.6 Improvement strategy and prospect of cat swarm optimization algorithm

3.6.1 Improvement strategy of cat swarm optimization algorithm

The improvement of cat swarm optimization algorithm mainly focuses on the normal increase of parameters and the addition of some operators, but there are few studies on the improvement of the algorithm framework and iterative evolution. Some scholars introduced PSO algorithm and chaos search and other algorithms or ideas into the cat swarm optimization algorithm, which to some extent improved the optimization performance of the algorithm. However, there are still some defects such as 'precocity' and slow running speed, and the introduced algorithm only performs a single behavior of the cat swarm optimization algorithm. The study of a discrete model for cat swarm optimization algorithm combinatorial optimization problem has not appeared yet.

1) Improved algorithm rules

To improve the convergence of cat swarm optimization algorithm, Orouskhani et al. [89] added a new parameter in the position update formula as the inertial weight and used the new rate update formula in the tracking model of the algorithm to propose a weighted average inertial cat swarm optimization algorithm. Yang et al. [90] proposed an improved chaotic cat swarm optimization algorithm for global optimization. By using different chaotic maps to improve the step size of the search model, seven different chaotic maps are studied to find the best logistics and sinusoidal graph.

2) Parallel algorithm

Solve the numerical optimization problem under the condition of small population size and less number of iterations, in the parallel cat group of the introduction of Taguchi method in the process of tracking algorithm, Tassi et al. [91] proposed a parallel optimization of high precision, fast computing-intensive cat swarm optimization algorithm, and applied it to solve the problem of the plane plan to restore, which achieved good application effect.

3) Hybrid algorithm

In order to solve the global optimization problem, Yang et al. [92] proposed a new cat swarm optimization algorithm inspired by homotopy algorithm. According to the dependent variable of the optimization function, a path from the simple problem solving to the problem solution given by homotopy algorithm is tracked. This strategy can improve the efficiency of cat swarm optimization algorithm.

3.6.2 Prospect of cat swarm optimization algorithm

The research of cat swarm optimization algorithm is just beginning, and some ideas are in the embryonic stage, the strict theoretical basis is not mature. The research on the idea, principle, parameter setting and population diversity of the algorithm is still in the experimental exploration stage without further analysis and discussion. The research on the analysis and proof of algorithm convergence has not appeared yet. Because of the shortcomings of the existing research results of cat swarm optimization algorithm and the problems existing in the algorithm itself, the future research work will focus on the following aspects:

1) To prove the convergence of the algorithm through analysis, and study or discuss the improvement strategy of cat swarm optimization algorithm.

2) To study the fusion technology and hybrid mode of cat swarm optimization algorithm and other intelligent algorithms (such as quantum evolutionary algorithm, multi-agent algorithm, simulated annealing algorithm, DE algorithm, etc.) on the overall framework.

3) Further, improve the algorithm, strengthen the theoretical basic research of cat swarm optimization algorithm, increase the diversity of the population, improve the adaptability of the algorithm to solve various optimization problems, and expand the application field of cat swarm optimization algorithm.

3.7 Improvement strategy and prospect of FA

3.7.1 Improvement strategy of FA

FA is an efficient optimization algorithm, which became the focus of many scholars and was well applied in many fields. However, standard FA cannot effectively solve different optimization problems. It has some defects such as slow convergence speed, low precision and high possibility of getting into local optimum which needs to be improved.

1) Based on adaptive strategy

Liu et al. [93] proposed the FA with adaptive characteristics of random parameters and absorption parameters, which improved the solution quality and convergence speed of the firefly algorithm.

2) Parameter adjustment

Farahani et al. [94] introduced an automatic learning machine in standard FA and enabling the algorithm to adjust parameter values according to the environment at any time. The experimental results show that the improved FA can greatly improve the optimization performance. FA based on parameter adjustment achieved better results than PSO algorithm in solving dynamic optimization problems.

3) Hybrid algorithm

Hassanzadeh et al. [95] proposed a new evolutionary optimization model cellular learning automata-firefly algorithm (CLA-FA). The new model is a combination of CLA and FA model. The new algorithm first improved the efficiency of the standard FA, and then the algorithm was combined with CLA. This method can effectively find the global optimal solution and improve the global search speed and search speed of the standard FA.

3.7.2 Prospect of FA

FA has the advantages of stability and strong global search ability, etc. Since the algorithm is proposed, it attracted the attention and research of many scholars and was constantly improved to obtain better optimization effect, but there are still some aspects to be further studied. Future research can be carried out in the following aspects:

1) The setting of parameters will affect the performance of FA. Finding efficient parameter control methods is an important direction of FA research.

2) Hybrid FA can overcome the disadvantages of FA itself to a certain extent and greatly improve the performance of the algorithm. At present, FA was integrated with GA, DE algorithm, Harmony search (HE) algorithm and other algorithms, and it is also one of the research hotspots to find a hybrid algorithm that can be effectively combined.

3) In terms of application, FA and its improved algorithm have been widely used in many fields, but there are few applications in classification and recognition. It is also meaningful to combine FA with machine learning. Besides, how to better solve the dynamic optimization problem with FA is also worth studying.

4) The mathematical theory of FA is not perfect, and the analysis of algorithm complexity and convergence is still of research significance.

3.8 Improvement strategy and prospect of BA

3.8.1 Improvement strategy of BA

BA has the shortcoming that it is easy to fall into the local optimum and lead to premature convergence, so many scholars have improved BA to obtain better results.

1) Improved algorithm rules

Tsai et al. [96] redefined the BA mode and random walk process, which improved the solution accuracy and shortened the calculation time compared with the standard BA.

2) Hybrid algorithm

Meng et al. [97] proposed a new bat algorithm (NBA). This algorithm integrated the habitat selection of bats and its adaptive compensation for Doppler effect into BA, and also added the adaptive local search strategy. The algorithm improved the efficiency and stability of BA. To solve the problems of slow convergence and low accuracy of BA, Xie et al. [98] proposed a new BA based on differential operator and Levy flight trajectory. The algorithm introduced a differential operator to improve the convergence speed of BA, and Levy flight trajectory can ensure the diversity of the population, avoid premature convergence, and make the algorithm effectively jump out of the local minimum. This new algorithm has better approximation ability in high dimensional space.

3.8.2 Prospect of BA

BA as a kind of intelligent optimization algorithm was widely applied to all kinds of optimization problems by using guidance strategies (such as the update of position and speed) to find the optimal solution in parallel in the problem search space. However, this algorithm also has some disadvantages such as premature convergence and low accuracy, which limits its application scope. The future research of BA will focus on the following aspects.

1) Parameter sensitivity. The influence of the change of values of different variables such as the attenuation coefficient of volume and the enhancement coefficient of search frequency on the convergence speed and result of the algorithm, based on summarizing the influence of parameter changes on the results, a more stable and superior improved BA is proposed.

2) Combination of BA and a local heuristic algorithm. BA adaptive random search is used to explore the potential optimal space. The local heuristic algorithm can explore the search space of BA in depth. The combination of two algorithms can achieve a balance between improving the convergence speed and seeking the optimal solution, thus jumping out of the local optimum and improving the solution accuracy.

3) BA is combined with other strategies, such as Doppler effect, chaotic bat, quantum behavior and so on.

3.9 Improvement strategy and prospect of WPA

3.9.1 Improvement strategy of WPA

WPA was not developed for a long time, it attracted the attention of other scholars because of its good performance. However, the algorithm also has some shortcomings, and scholars made a lot of research to improve it. The following improvement strategy can be summarized in their paper.

1) Improved search strategy

Liang et al. [99] formulated a cluster cooperative rule based on the principle of dynamic wolf head alternation and real-time role assignment and proposed a fatigue-rendering tactic based on interception strategy in two teams. Then, the clustering cooperative rule enlightened by the group's behavior is established, and the convergence of the algorithm is proved with the Markov asymptotic convergence theory. The method can effectively guarantee the efficiency of solving large-scale complex optimization problems and the operational effectiveness of distributed cluster cooperative attack problems.

2) Hybrid algorithm

In Ref. [100], a new hybrid optimization algorithm based on wolf pack search and local search (WPS-LS) is proposed for traveling salesman problem. The new algorithm firstly simulated the predatory process of wolf pack from the broad field to a specific place so that it allows for a search through all possible solution spaces and prevents wolf individuals from getting trapped into local optimum. Then, the local search operation is used in the algorithm to improve the speed of solving and the accuracy of the solution.

3.9.2 Prospect of WPA

Although the WPA has many advantages over other bionic intelligent algorithms in solving complex optimization problems, the algorithm also exposed many shortcomings in the process of solving the actual problem. Therefore, the future research of WPA can be carried out from the following aspects:

1) The performance of WPA is easily affected by the size of parameter values. How to properly set the size of each parameter value or the size of the self-adaptive set parameter value according to different optimization problem to minimize the unsatisfactory setting of parameter values and avoid to affect the performance of WPA.

2) The convergence speed late decreased obviously, which is likely to be fierce wolf behavior caused by the poor efficiency of a siege, the size of the siege of strength also reflected the wolves the strength of the local searchability of the algorithm, how to balance or strengthen the wolves global search ability and local searchability of the algorithm, the wolves in the searching efficiency of the algorithm further, will be one of the focus of the later research.

3) As a bionic intelligent algorithm, WPA has obvious characteristics of biological society and relatively weak mathematical support, requiring profound theoretical analysis and mathematical proof.

3.10 Improvement strategy and prospect of chicken swarm optimization algorithm

3.10.1 Improvement strategy of chicken swarm optimization algorithm

Since the chicken swarm optimization algorithm was proposed, many experts and scholars have studied and improved the algorithm's shortcomings, such as low solution accuracy and weak local searchability. At the same time, the application of the chicken swarm optimization algorithm to many practical problems in many fields has largely made up for the shortcomings of the algorithm.

1) Improved algorithm rules

Chen et al. [101] proposed an improved boundary chicken swarm optimization algorithm solve the parameter estimation problem of nonlinear systems. Qu et al. [102] replaced the Gaussian distribution in the rooster position with the adaptive T-distribution and added the elite reverse learning strategy in the hen position. Finally, the improved algorithm was simulated and analyzed. Chen et al. [103] combined the modified chicken swarm optimization algorithm with the dynamic penalty function to solve the nonlinear constraint optimization problem and compared it with other algorithms.

2) Parameter adjustment

Wu et al. [104] proved the convergence of the algorithm, analyzed the important parameters of the algorithm in detail, and proposed an improved algorithm to improve the convergence accuracy and speed of the algorithm in solving the high-dimensional optimization problem.

3) Hybrid algorithm

Liang et al. [105] proposed a hybrid algorithm to optimize the amplitude of the linear antenna array, the amplitude and spacing of the ring antenna array element by combining the advantages of the cuckoo search algorithm and chicken swarm optimization algorithm.

3.10.2 Prospect of chicken swarm optimization algorithm

Chicken swarm optimization algorithm is a new intelligent swarm optimization algorithm which was proposed in recent years. The research and application of chicken swarm optimization algorithm is still a hot spot. Although the research result is few, there is still a lot of literature worth referring to. Many scholars made some studies on the improvement and application of chicken swarm optimization algorithm, there are still many problems in chicken swarm optimization algorithm that need to be further studied.

1) Theoretical proof. Chicken swarm optimization algorithm was not been proposed for a long time. The convergence proof of the updated formulas of rooster, hen and chick and the convergence analysis of the whole algorithm is the focus of future research.

2) Parameter determination of chicken swarm optimization algorithm. The selection of parameters has a great impact on the performance of chicken swarm optimization algorithm. How to select parameters is mainly based on prior experience. How to better determine the parameters of the algorithm should be further studied.

3) Effective application of the algorithm in other fields. Because of its strong self-organization, cooperation, self-adaptation force, and other advantages have been successfully used to solve a variety of problems, but there are still many application fields and practical problems need to be further solved, such as multi-objective problem, graph coloring problem and travel agent problem and so on.

4 Conclusions

As a kind of natural heuristic algorithm, swarm intelligent optimization algorithms cannot only solve almost any complex optimization problems but also be applied to solve life problems in engineering practice. With the rapid development of computer technology, various bionic algorithms spring up like mushrooms. The paper studies swarm intelligence optimization algorithm based on bionics and lists almost all swarm intelligence optimization algorithms in chronological order. Firstly, the basic principles, advantages, and defects of various algorithms are described, and their application fields are enumerated. Then the improvement strategies of each algorithm are explained. Finally, each algorithm was prospected. This paper systematically expounds the related theories of swarm intelligence optimization algorithm based on bionics, which is not only suitable for beginners to learn basic principles but also suitable for scholars with certain basic knowledge to conduct in-depth research.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (61601177), and the Science and Technology Research Program of Hubei Provincial Department of Education (Q20171401).

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