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Artificial fish swarm algorithm: a survey of the state-of-the-art, hybridization, combinatorial and indicative applications

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Abstract AFSA (artificial fish-swarm algorithm) is one of the best methods of optimization among the swarm intelligence algorithms. This algorithm is inspired by the collective movement of the fish and their various social behaviors. Based on a series of instinctive behaviors, the fish always try to maintain their colonies and accordingly demonstrate intelligent behaviors. Searching for food, immigration and dealing with dangers all happen in a social form and interactions between all fish in a group will result in an intelligent social behavior. This algorithm has many advantages including high convergence speed, flexibility, fault tolerance and high accuracy. This paper is a review of AFSA algorithm and describes the evolution of this algorithm along with all improvements, its combination with various methods as well as its applications. There are many optimization methods which have a affinity with this method and the result of this combination will improve the performance of this method. Its disadvantages include high time complexity, lack of balance between global and local search, in addition to lack of benefiting from the experiences of group members for the next movements.

Keywords Artificial fish swarm optimization · Swarm optimization · Natural computing

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1 Introduction

Most species of animals show social behaviors. In some species this is the top member of the group which leads all members of that group. For example, this behavior is very apparent in lions, monkeys and deer. However, there are other kinds of animals which live in groups but have no leader. In this type of animals each member has a self organizer behavior which enables it to move around its environment and response to its natural needs with no need to leader like birds, fishes and sheep droves. This type of animals has no knowledge about their group and environment. Instead, they can move in the environment via exchanging data with their adjacent members. This simple interaction among particles makes group behavior more sophisticated as if we are looking for a particle in a wide environment.

This review considers artificial fish swarm optimization (AFSO), a relatively recent addition to the field of natural computing, that has elements inspired by the social behaviors of natural swarms, and connections with evolutionary computation. AFSO has found widespread application in complex optimization domains, and currently a major research topic, offering an alternative to the more established evolutionary computation techniques that may be applied in many of the same domains.

This paper review the artificial fish-swarm algorithm (AFSA), its evolution stages from the start point up to now, improvements and applications in various fields like optimization, control, image processing, data mining, improving neural networks, networks, scheduling, and signal processing and so on. Also, various methods combining the AFSA with other optimization methods like PSO, Fuzzy Logic, Cellular Learning Automata or intelligent search methods like Tabu search, Simulated Annealing, Chaos Search and etc.

This paper is structured as follow. Section two briefly reviews the general formulation of AFSO. Section three reviews the improved of AFSO. Section four reviews the motivations for, and research into, hybrid algorithms, many of which involve evolutionary techniques. Section four highlights some recent research into the application of AFSO to combinatorial problems. Section five concludes.

2 General formulation

In nature, the fish can discover the more nutritious area by individual search or following after other fish, the area with much more fish is generally most nutritious. The basic idea of the AFSO is to imitate the fish behaviors such as praying, swarming, and following with local search of fish individual for reaching the global optimum (Li 2003). The environment where a AF lives is mainly the solution space and is the states of other AFs. Its next behavior depends on its current state and its local environmental state (including the quality of the question solutions at present and the states of nearby companions). An AF would influence the environment via its own activities and its companions' activities.

A new evolutionary computation technique, AFSO was first proposed in 2002 (Li et al.). AFSO possess similar attractive features of genetic algorithm (GA) such as independence from gradient information of the objective function, the ability to solve complex nonlinear high dimensional problems. Moreover, they can achieve faster convergence speed and require few parameters to be adjusted. Whereas the AFSO does not possess the crossover and mutation processes used in GA, so it could be performed more easily. AFSO is also a Optimizer based on population. The system is started first in a set of randomly generated potential solutions, and then performs the search for the optimum one interactively (Zhang et al. 2006).

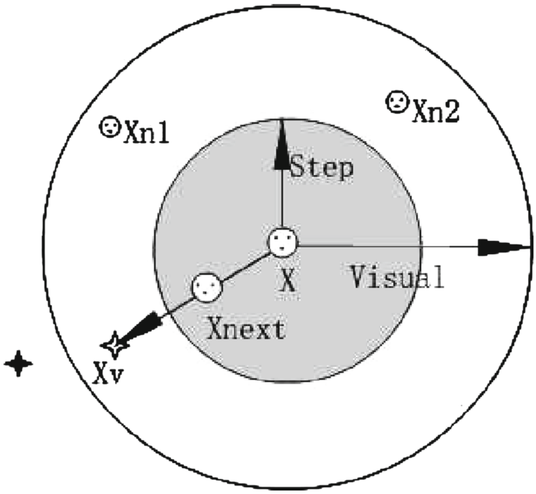

Fig. 1 Vision concept of the artificial fish

Artificial fish (AF) is a fictitious entity of true fish, which is used to carry on the analysis and explanation of problem, and can be realized by using animal ecology concept. With the aid of the object-oriented analytical method, we can regard the artificial fish as an entity encapsulated with one's own data and a series of behaviors, which can accepts amazing information of environment by sense organs, and do stimulant reaction by the control of tail and fin. The environment in which the artificial fish lives are mainly the solution space and the states of other artificial fish. Its next behavior depends on its current state and its environmental state (including the quality of the question solutions at present and the states of other companions), and it influences the environment via its own activities and other companions' activities (Jiang et al. 2007).

The AF realizes external perception by its vision showed in Fig. 1. X is the current state of a AF, Visual is the visual distance, and X_v is the visual position at some moment. If the state at the visual position is better than the current state, it goes forward a step in this direction, and arrives the X_{next} state; otherwise, continues an inspecting tour in the vision. The greater number of inspecting tour the AF does, the more knowledge about overall states of the vision the AF obtains. Certainly, it does not need to travel throughout complex or infinite states, which is helpful to find the global optimum by allowing certain local optimum with some uncertainty.

Let $X = (x_1, x_2, \ldots, x_n)$ and $X_v = (x^v{}_1, x^v{}_2, \ldots, x^v{}_n)$ then this process can be expressed as follows:

$$x_i^v = x_i + Visual.rand\,(), \quad i \in (0, n] \tag{1}$$

$$X_{next} = X + \frac{X_v - X}{\|X_v - X\|}.Step.rand(). \tag{2}$$

where *Rand ()* produces random numbers between zero and 1, *Step* is the step length, and x_i is the optimizing variable, n is the number of variables. The AF model includes two parts (variables and functions). The variables include: X is the current position of the AF, *Step* is the moving step length, *Visual* represents the visual distance, *try_number* is the try number and δ is the crowd factor ($0 < \delta < 1$). The functions include the behaviors of the AF: AF_Prey, AF_Swarm, AF_Follow, AF_Move, AF_Leap and AF_Evaluate.

2.1 The basic functions of AFSA

Fish usually stay in the place with a lot of food, so we simulate the behaviors of fish based on this characteristic to find the global optimum, which is the basic idea of the AFSO. The basic behaviors of AF are defined (9, 10) as follow for maximum:

(1) AF_Prey: This is a basic biological behavior that tends to the food; generally the fish perceives the concentration of food in water to determine the movement by vision or sense and then chooses the tendency. Behavior description: Let X_i be the AF current state and select a state Xj randomly in its visual distance, Y is the food concentration (objective function value), the greater *Visual* is, the more easily the AF finds the global extreme value and converges.

$$X_j = X_i + Visual.rand\,() \tag{3}$$

If $Y_i < Y_j$ in the maximum problem, it goes forward a step in this direction;

$$X_i^{(t+1)} = X_i^{(t)} + \frac{X_j - X_i^{(t)}}{\left\| X_j - X_i^{(t)} \right\|}.Step.rand(). \tag{4}$$

Otherwise, select a state Xj randomly again and judge whether it satisfies the forward condition. If it cannot satisfy after *try_number* times, it moves a step randomly. When the *try_number* is small in AF_Prey, the AF can swim randomly, which makes it flee from the local extreme value field.

$$X_i^{(t+1)} = X_i^{(t)} + Visual.rand\,() \tag{5}$$

(2) AF_Swarm: The fish will assembles in groups naturally in the moving process, which is a kind of living habits to guarantee the existence of the colony and avoid dangers. Behavior description: Let Xi be the AF current state, Xc be the center position and n_f be the number of its companions in the current neighborhood ($d\,ij$ < Visual), n is total fish number. If $Yc > Yi$ and $\frac{n_f}{n} < \delta$, which means that the companion center has more food (higher fitness function value) and is not very crowded, it goes forward a step to the companion center;

$$X^{(t+1)}{}_i = X_i^{(t)} + \frac{X_c - X_i^{(t)}}{\left\| X_c - X_i^{(t)} \right\|}.Step.rand(). \tag{6}$$

Otherwise, executes the preying behavior. The crowd factor limits the scale of swarms, and more AF only cluster at the best area, which ensures that AF move to optimum in a wide field.

(3) AF_Follow: In the moving process of the fish swarm, when a single fish or several ones find food, the neighborhood partners will trail and reach the food quickly. Behavior description: Let Xi be the AF current state, and it explores the companion Xj in the neighborhood ($d\,ij$ <Visual), which has the greatest Yj. If $Yj > Yi$ and $\frac{n_f}{n} < \delta$, which means that the companion Xj state has higher food concentration (higher fitness function value) and the surrounding is not very crowded, it goes forward a step to the companion Xj,

$$X^{(t+1)}{}_i = X_i^{(t)} + \frac{X_j - X_i^{(t)}}{\left\| X_j - X_i^{(t)} \right\|}.Step.rand(). \tag{7}$$

Otherwise, executes the preying behavior.

(4) AF_Move: Fish swim randomly in water; in fact, they are seeking food or companions in larger ranges.

Behavior description: Chooses a state at random in the vision, then it moves towards this state, in fact, it is a default behavior of AF_Prey.

$$X_i^{(t+1)} = X_i^{(t)} + Visual.rand\,() \tag{8}$$

(5) AF_Leap: Fish stop somewhere in water, every AF's behavior result will gradually be the same, the difference of objective values (food concentration, FC) become smaller within some iterations, it might fall into local extremum change the parameters randomly to the still states for leaping out current state.

Behavior description: If the objective function is almost the same or difference of the objective functions are smaller than a proportion during the given $(m-n)$ iterations, Chooses some fish randomly in the whole fish swarm, and set parameters randomly to the selected AF. The β is a parameter or a function that can makes some fish have other abnormal actions (values), *eps* is a smaller constant.

$$\begin{aligned} &if\,(BestFC(m) - BestFC(n)) < eps \\ &X_{some}^{(t+1)} = X_{some}^{(t)} + \beta.Visual.rand\,() \end{aligned} \tag{9}$$

AF_Swarm makes few fish confined in local extreme values move in the direction of a few fishes tending to global extreme value, which results in AF fleeing from the local extreme values. AF_Follow accelerates AF moving to better states, and at the same time, accelerates AF moving to the global extreme value field from the local extreme values.

3 Improved AFSO

ASFA is one of the best Swarm Intelligence algorithms. However, it has disadvantages including:

Higher time complexity, lower convergence speed, lack of balance between global search and local search, and not use of the experiences of group members for the next moves. It has many advantages, such as good robustness, global search ability, tolerance of parameter setting, and it is also proved to be insensitive to initial values. In recent years many researchers have tried to improve this algorithm. In this section, we investigate the various improvements made in this algorithm. Despite all its advantages, AFSA algorithm has also some weaknesses. Using different algorithms and synthesizing them with AFSA, different researchers have tried to improve this method. Some of these synthetic methods are reviewed in this paper.

3.1 The improved basic behaviors in AFSO1 (Jiang et al. 2009)

To enhance the performance of the AFSO1 (Jiang et al. 2009), the information of global best AF is added to the behaviors of the AF. The realization of the behaviors in IAFSA is as follow for minimum:

(1) Praying behavior (*AF_Prey*):

Let X_i be the AF current state and select a state X_j randomly within visual distance, $Y = f(\mathbf{X})$ is the food consistence of an AF:

$$X_j = X_i + af\_visual.rand() \tag{10}$$

If $Y_i < Y_j$ in the minimum problem, it goes forward a step in the direction of the vector sum of the X_j and the X_{best_af}, X_{best_af} is the best AF state in all AFs till now.

$$X_i^{t+1} = X_i^t + \left(\frac{X_j - X_j^t}{\left\| X_j - X_j^t \right\|} + \frac{X_{best\_af} - X_i^t}{\left\| X_{best\_af} - X_i^t \right\|} \right) * af\_step * rand() \tag{11}$$

Otherwise, select a state X_j randomly again and judge whether it satisfies the forward requirement. If the forward requirement cannot be satisfied after *try _ number* times, the AF would move a step randomly; this can help the AF flee from the local extreme field.

$$X_i^{t+1} = X_i^t + af\_visual * rand() \tag{12}$$

(2) Swarming behavior (*AF_Swarm*):

Let X_i be the AF current state, X_c be the center position of several AF and n_f be the number of its companions within the AF's visual range. If $Y_c < Y_i$ and $Y_c < af\_delta * Y_i/n_f$, which means that the fellow center has lower fitness value and the surrounding environment is not very crowded, and then the AF goes forward a step in the direction of the vector sum of the X_c and the X_{best_af}.

$$X_i^{t+1} = X_i^t + \left(\frac{X_c - X_i^t}{\left\| X_c - X_i^t \right\|} + \frac{X_{best\_af} - X_i^t}{\left\| X_{best\_af} - X_i^t \right\|} \right) * af\_step * rand() \tag{13}$$

Otherwise, the preying behavior is executed.

(3) Following behavior (*AF_Follow*):

Let X_i denote the AF current state, and the AF explores its neighborhood area to find the AF X_j which has the smaller Y_j. If $Y_j < Y_i$ and $Y_j < af\_delta * Y_i/n_f$, which means that the AF X_j has lower fitness value and the surrounding environment is not very crowded, the AF X_i goes forward a step in the direction of the vector sum of the X_j and the X_{best_af}.

$$X_i^{t+1} = X_i^t + \left(\frac{X_j - X_i^t}{\left\| X_j - X_i^t \right\|} + \frac{X_{best\_af} - X_i^t}{\left\| X_{best\_af} - X_i^t \right\|} \right) * af\_step * rand() \tag{14}$$

(4) Moving behavior (*AF_Move*):

The AF chooses a state randomly within the visual range, and then it moves towards this state, it is a default behavior of an AF.

$$X_i^{t+1} = X_i^t + af\_visual * rand() \tag{15}$$

(5) Other behaviors

Other behaviors of IAFSO1 such as leaping behavior and evaluating behavior are the same as AFSO. The leaping behavior (Jiang et al. 2007) is proposed to increase the probability to leap out local extremes. The evaluating behavior is based on the evaluation to the environment of an AF, and can help the AF select a proper behavior to execute. The swallowing behavior (Cheng et al. 2009) is executed if the fitness function value is bigger (for minimum optimization) than a given threshold in updating process of AFSO.

Experimental results show that the IAFSO1 has advantages of faster convergence speed and higher global search accuracy than the standard AFSO by adding limited computing complexity, because of its good performance, the IAFSO1 might replace the AFSO in future optimization applications.

Table 1 Optimization results of test functions

Function	Minimum	CAFAC	CAFA	AFA
Ackley	0	1.1902×10^{-14}	0.0856	1.3702
CM	-3	-2.7488	-2.3564	-0.3397
DejongF4	0	2.2424×10^{-69}	0.0015	0.1799
Expfun	1	1.0000	1.0107	1.4584
Griewank	0	0	5.1764×10^{-4}	0.0262
Hyperelliptic	0	3.0539×10^{-25}	1.1758	92.0497
LM1	0	5.0237×10^{-17}	0.0152	0.4314
LM2	0	7.9746×10^{-16}	0.0351	0.1954
Neumaier	-4930	-4.9135×10^{3}	-1.4474×10^{3}	-1.2359×10^{3}
Sphere	0	4.2319×10^{-20}	0.0147	0.4546

Table 2 Mean squared error value

	1000	2000	3000	4000	5000	Mean value	Covariance
BP	0.254321	0.1387986	0.0897689	0.0587654	0.013212	0.1109	0.109
AFSA	0.136921	0.0591478	0.0388571	0.0211594	0.008199	0.087	0.161
IAFSA	0.086795	0.0482575	0.0143682	0.0124046	0.000073	0.062	0.103

3.2 Cultured artificial fish-swarm algorithm (CAFAC) (Gao et al. 2010)

A novel cultured AFSA with the crossover operator, namely CAFAC (Gao et al. 2010), is proposed to enhance its optimization performance. The crossover operator used is to promote the diversification of the artificial fish and make them inherit their parents' attributes. The Culture Algorithms (CA) is also joined with the AFA so that the blind search can be struggled with.

In the CAFAC, a crossover operator is used to improve the diversification of the artificial fish and make the artificial fish inherit their parents' characteristics. The CA is farther combined with the adjusted AFA together to overcome the shortcoming of blind search. A total of ten high-dimension and multi-peak functions are employed to examine the performance of our CAFAC. Simulation results show that it can indeed outperform the original AFA.

In order to study the performance of the proposed CAFAC, ten nonlinear functions have been used to inspect its optimization capability. All these functions, as given in Table 1, are multi-modal functions with a lot of local optima around their global optima. The CAFAC is compared with both the CAFA and AFA, and the results are provided in Table 2. They emphasize that the optimization results obtained here are the average of 100 independent trials, and the number of iterations is 1,000 in each trial. The parameters of the three algorithms are selected as: Visual = 250, step = 225, $\delta = 24$, and *trynumber* = 10. Table 1 shows that the CAFAC can yield significant improvements in optimization performance compared with both the CAFA and AFA for all the 10 functions. Figures 2 and 3 illustrate the comparison of convergence speeds among the three algorithms. As an illustrative example, Fig. 3 shows the optimization results of the Griewank function. After about 900 iterations, the CAFCA algorithm has nearly found the global optimum: zero. Note that the logarithmic (base 10) scale is used for the vertical axis. On the other hand, from the figures, it can be discovered

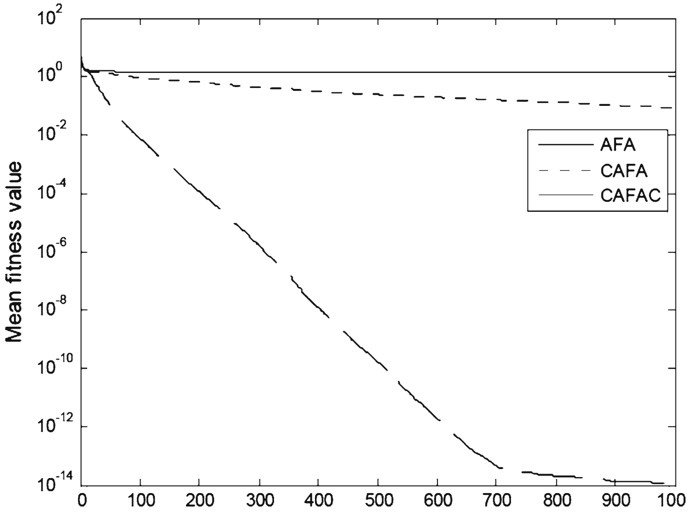

Fig. 2 Optimization results of Ackley function

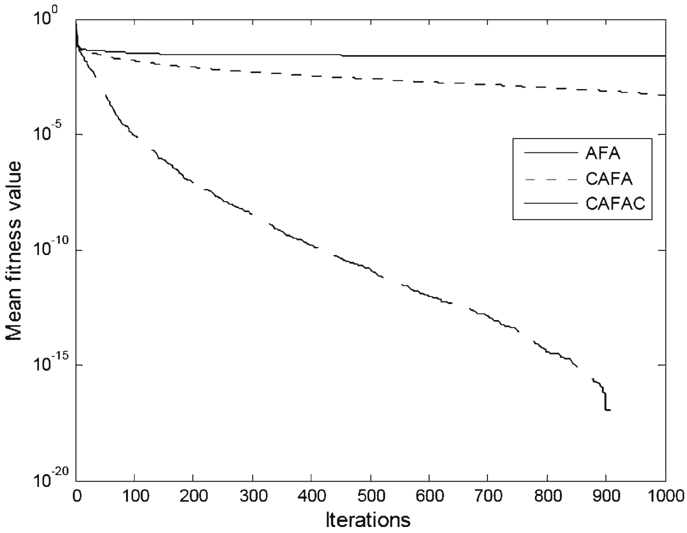

Fig. 3 Optimization results of Griewank function

that both the CAFA and AFA suffer from the premature convergence when applying to the high dimension functions. In brief the CAFAC can successfully locate the global optimum with a faster convergence speed.

3.3 Improved artificial fish-swarm optimization (IAFSO2) (Wang et al. 2005)

In order to improve the algorithm's stability and the ability to search the global optimum, they propose an improved AFSO (IAFSO) (Wang et al. 2005). When the artificial fish swarm's optimum value is not difference after defined generations, they add leaping behavior and change the artificial fish parameter randomly. Incidentally, they can increase the probability to obtain the global optimum.

3.3.1 The elimination of step restriction

In the AFSO, the step of artificial fish is a random number in (0, step) while they perform searching behavior, swarming behavior and chasing behavior. The three AF's behaviors are local actions which increase the likelihood of individual evolution and premature. The actual step of IAFSO2 is a random number in the defined area to guarantee the better global search capacity.

3.3.2 The leaping behavior

The searching behavior, swarming behavior and chasing behavior are all local behaviors in some degree. If the objective functions value is not changed after several iterations, it manifests that the function might fall into local minimum. If the program continues iterating, every AF's result will progressively be same and the probability of leaping out local optimum will be smaller. To increase the probability to leap out local optimum and reach global optimum, they try to add leaping behavior to AF.

The AF's leaping behavior is defined as follow. If the objective value's difference among K times and K + N times is smaller than *eps* in the iteration process, they select randomly an AF according to the ratio $p(0 < p < 1)$ and change its parameters randomly in the defined area.

AFSO is a novel method to search global optimal value by AF's searching behavior, swarming behavior and chasing behavior. The step constrains in the three behaviors affects the global search capacity for the AF. Therefore, they remove the step constraint in IAFSO2. In addition, they add leaping behavior to AFSO in order to reduce the possibility of AF falling into local optimum. They make plans for the data structure and procedure in order to apply AFSO and IAFSO2 to the training process of three layouts feed-forward neural networks and the comparison result exhibits that the IAFSO2 has better global severity and stability.

So, the improvement of AFSO in the paper is effective, and IAFSO2 is an effective method to train feed-forward neural networks.

In this research, BP algorithm was used, AFSA and IAFSA to train the three feed-forward neural networks. The testing data have been conducted as shown in Tabel2. In the experiment, the structure of three layer feed-forward neural networks is 13-15-9 and the AF's number is 30. At the same time, parameter were defined as follows: visual = 0.9, NUM = 5,000, $\delta = 3.618$ and STEP = 0.5 in AFSA and IAFSA, and in AFSA.

The results computed by BP algorithm, AFSA and IAFSA every 1,000 times are shown in Table 2. The Fig. 4 shows the difference of error value obtained by 5,000 iterations with AFSA and IAFSA. The error values computed by AFSA and IAFSA are better than those gotten by BP algorithm in Table 2.

3.4 Improved artificial fish-swarm optimization (IAFSO3) (Fernandes et al. 2009)

The algorithm here presented is a modified version of the artificial fish swarm algorithm for global optimization (Fernandes et al. 2009). The new ideas are focused on a set of movements, closely related to the random, the searching and the leaping fish behaviors. An expansion to bound restricted problems is also presented. To estimate the performance of the new fish swarm intelligent algorithm, a set of seven benchmark problems are used. A sensitivity analysis regarding some of the user defined parameters is presented.

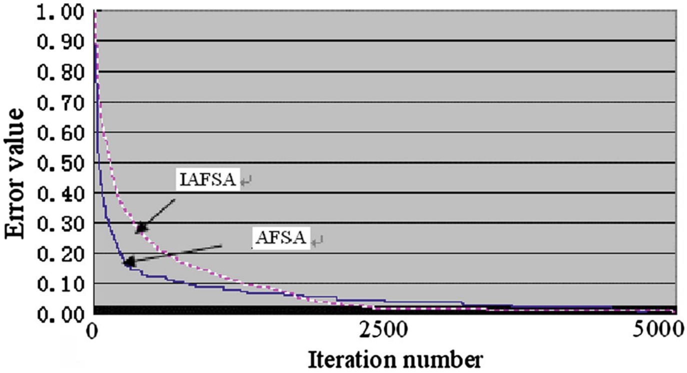

Fig. 4 The comparison result between IAFSA and AFSA

They present a new version of the artificial fish swarm algorithm, here denoted by fish swarm intelligent (FSI) algorithm. Their modifications are focused on:

1. The extension to bound constrained problems meaning that any fish movement will be maintained inside the bounds along the iterative process;
2. Modified procedures to translate random, searching and leaping fish behaviors;
3. The introduction of a selective procedure;
4. Different termination conditions.

The four main algorithms are shown in the Table 3.

Here, three values were combined of δ, namely 0:1,1 and 10, with two values of θ : 0:8 and 1. The value of μ_δ was maintained fixed as 0:9. Figure 5 present plots with the best function value, the average function value and the worst function value obtained after 10 runs, for the seven problems. The results in Fig. 5 reveal that the consistency of solution is higher when $\theta = 1$ for some problems and when $\theta = 0.8$ for others.

4 Hybrid AFSO

Despite of its many advantages, the AFSA has some disadvantages. Different researchers have tried to improve this algorithm by using different algorithm and combining them with this algorithm. In this paper, some of these composite approaches are reviewed.

4.1 CF-AFSA

A hybrid artificial fish swarm algorithm, which is combined with CF and artificial fish swarm algorithm, is proposed in this research to solve the Bin packing problem. Experiment results compared with GA shows that the hybrid artificial fish swarm algorithm has a good performance with broad and successful application (Wang and Ma 2011).

The dimension of search space is established as n, the scale of fish N. Each artificial fish can be expressed as a vector of n dimension $X_i = (x_{i1}, x_{i2}, \ldots, x_{in})(i = 1, 2, \ldots, N)$; function $Y = f(X)$ shows the current concentration of food of artificial fish; $d_{i,j} = d(X_i, X_j)(i, j = 1, 2, \ldots, N)$ *means* the distance between the artificial fish X_i and the artificial fish X_j; δ signifies congestion degree factor; *TryNumber* shows the largest trying number of each movement of artificial fish; *Visual* means the field of vision of artificial fish.

Table 3 The four main algorithms

Algorithm 2 *Random*

input: x^i, l, u, "visual"
for $k = 1, \ldots, n$ **do**
  $\lambda_1 \sim U[0,1]$; $\lambda_2 \sim U[0,1]$
  if $\lambda_1 > 0.5$ **then**
    if $u_k - x_k^i >$ "visual" **then**
      $y_k = x_k^i + \lambda_2$ "visual"
    else
      $y_k = x_k^i + \lambda_2(u_k - x_k^i)$
    end if
  else
    if $x_k^i - l_k >$ "visual" **then**
      $y_k = x_k^i - \lambda_2$ "visual"
    else
      $y_k = x_k^i - \lambda_2(x_k^i - l_k)$
    end if
  end if
end for

Algorithm 3 (Movement along a particular direction)

input: x^i, l, u, d^i
$\lambda \sim U[0,1]$
for $k = 1, \ldots, n$ **do**
  if $d_k^i > 0$ **then**
    $y_k^i \leftarrow x_k^i + \lambda \frac{d_k^i}{\|d^i\|}(u_k - x_k^i)$
  else
    $y_k^i \leftarrow x_k^i + \lambda \frac{d_k^i}{\|d^i\|}(x_k^i - l_k)$
  end if
end for

Algorithm 4 (Leaping behavior)

input: x, l, u
rand $\sim U\{1, \ldots, m\}$
for $k = 1, \ldots, n$ **do**
  $\lambda_1 \sim U[0,1]$; $\lambda_2 \sim U[0,1]$
  if $\lambda_1 > 0.5$ **then**
    $y_k = x_k^{\text{rand}} + \lambda_2 (u_k - x_k^{\text{rand}})$
  else
    $y_k = x_k^{\text{rand}} - \lambda_2 (x_k^{\text{rand}} - l_k)$
  end if
end for

Algorithm 1 fish swarm intelligent algorithm

Input: m, l, u, $nfe_{\max}$, ε, δ, μ_δ, θ, η
iteration $\leftarrow 1$; $\tau \leftarrow 1$
$(x^1, \ldots, x^m) \leftarrow$ *Initialize*()
while termination criteria are not satisfied **do**
  for $i = 1, \ldots, m$ **do**
    Compute the "visual"
    if *visual scope* is empty **then**
      $y^i \leftarrow$ *Random*(x^i)
    else
      if *visual scope* is crowded **then**
        $y^i \leftarrow$ *Search*(x^i)
      else
        if central point is better than x^i **then**
          $y_1^i \leftarrow$ *Swarm*(x^i)
        else
          $y_1^i \leftarrow$ *Search*(x^i)
        end if
        if best function value is better than $f(x^i)$ **then**
          $y_2^i \leftarrow$ *Chase*(x^i)
        else
          $y_2^i \leftarrow$ *Search*(x^i)
        end if
        $y^i \leftarrow \arg\min\{f(y_1^i), f(y_2^i)\}$
      end if
    end if
  end for
  for $i = 1, \ldots, m$ **do**
    $x^i \leftarrow$ *Select*(x^i, y^i)
  end for
  if iteration $> \tau m$ **then**
    if "stagnation" occurs **then**
      Randomly choose a point x^i
      $y^i \leftarrow$ *Leap*(x^i)
    end if
    $\tau \leftarrow \tau + 1$
    $\delta = \mu_\delta \delta$
  end if
  iteration $\leftarrow$ iteration + 1
end while

4.1.1 The description of algorithm

Step 1: Initialization
Step 2: Calculate fitness value
Step 3: Each artificial fish $i \quad (i = 1, 2, \ldots, N)$
Step 3.1: Following; judge whether the state after following is better than the previous state, and if so, turn to.
Step 4, otherwise turn to Step 3.2;
Step 3.2: Clustering; judge whether the state after clustering is better than the previous state, and if so, turn to.
Step 4, otherwise turn to Step 3.3;
Step 3.3: Foraging;
Step 4: Update the current best value;
Step 5: Update the distance among fish swarm $d_{i,j}$, $(i, j = 1, 2, \ldots, N)$
Step 6: If already achieve the maximum evolution algebra, exit; otherwise, turn to Step 3.

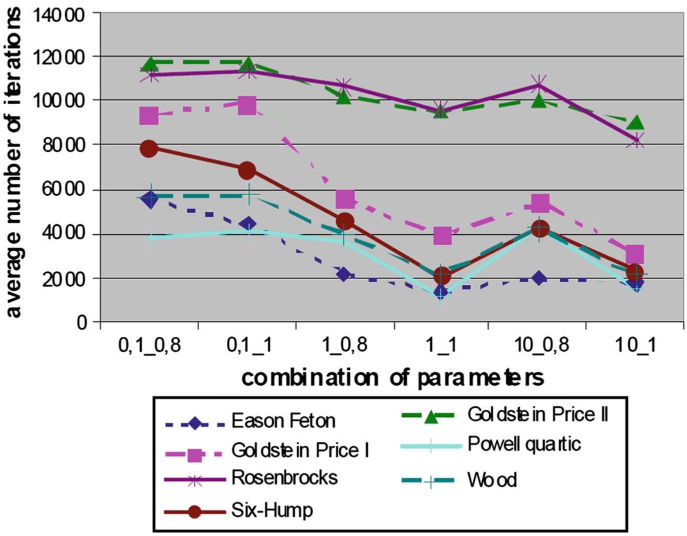

Fig. 5 Combination of δ and θ with fixed $\mu_\delta = 0.9$

4.2 AFSA-PSO (HAP)

A hybrid of artificial fish swarm algorithm (AFSA) and particle swarm optimization (PSO) is used to training feed forward neural network. After the two algorithms are introduced respectively, the hybrid algorithm based on the two is expressed. The hybrid not only has the artificial fish behaviors of swarm and follow, but also takes advantage of the information of the particle. An experiment with a function approximation is simulated, which proves that the hybrid is more effective than AFSA and PSO (Huadong et al. 2007).

4.2.1 Behavior of searching food

In general, the fish stroll at random. When the fish discover a water area with more food, they will go quickly toward the area. Let us presume that *Xi* is the AF state at present, and $Xj \in S$. The behavior of follow can be expressed as the following:

$$prey(X_i) = \begin{cases} X_i + step\frac{X_j - X_i}{\|X_j - X_i\|} & if\ y_j > y_i \\ X_i + step & else \end{cases} \tag{16}$$

4.2.2 Behavior of swarm

In the process of swimming, the fish will swarm spontaneously in order to share the food of the swarm. Let us assume that *Xi* is the AF state at present, and $X_c = \sum_{x \in s} X_j / nf$. The behavior of swarm to AF i can be expressed in Formula 4.

$$swarm(X_i) = \begin{cases} X_i + step\frac{X_c - X_i}{\|X_c - X_i\|} & if\ \frac{y_c}{nf} > \delta y_i \\ pery(X_i) & else \end{cases} \tag{17}$$

4.2.3 Behaviors of agents

When one fish of the fish swarm discovers more food, the other fish will share with it. Let us assume that *Xi* is the AF state at present, and $y_{\max} = \max\{f(X_i)|X_j \in S\}$. The behavior of follow can be expressed in Formula 5.

$$follow(X_i) = \begin{cases} X_i + step\frac{X_{\max}-X_i}{\|X_{\max}-X_i\|} & if\ \frac{y_{\max}}{nf} > \delta y_i \\ pery(X_i) & else \end{cases} \tag{18}$$

According to the character of the problem, the AF evaluates the environment at present, and then selects an appropriate behavior. For example, behaviors of follow and swarm are both simulated, the better of improved its state will be executes. This process indicates the flexibility of AFSA.

MFNN training by a new algorithm, HAP, is proposed. HAP is a hybrid of PSO and AFSA; it has the advantages of the two at the same time. When the information of the AFSA is enough, AFSA will be executed, and otherwise, the PSO will be executed. With the above performance, HAP is a good algorithm to training MFNN. To demonstrate the performance of HAP, designs of function approximation with three layers ANN are simulated.

4.3 AFSA-SFLA

In order to overcome the defects of shuffled frog leaping algorithm (SFLA) such as slow searching speed in the late evolution and easily trapping into local extremum, a composite shuffled frog leaping algorithm (CSFLA) based on the basic idea of artificial fish-swarm algorithm (AFSA) is put forward in this paper in which the follow behavior of fish swarm is used to accelerate the optimization speed and the swarm behavior to improve the capacity for out of local extremum. The test results show that CSFLA increases the convergence velocity outstandingly and enhances the global searching performance effectively (Zhang et al. 2010).

4.4 AFSA-CLA

A new algorithm which is obtained by hybridizing cellular learning automata and artificial fish swarm algorithm (AFSA) is proposed for optimization in continuous and static environments. In the proposed algorithm, each dimension of search space is assigned to one cell of cellular learning automata and in each cell a swarm of artificial fishes are located which have the optimization duty of that specific dimension. In fact, in the proposed algorithm for optimizing D-dimensional space, there are D one-dimensional swarms of artificial fishes that each swarm is located in one cell and they contribute with one another to optimize the D-dimensional search space. The learning automata in each cell are responsible for making diversity in artificial fish swarm of that dimension and equivalence between global search and local search processes. The proposed algorithm with standard AFSA, Cooperative Particle swarm optimization (PSO) and global version of PSO in 10- and 30-dimensional spaces are practiced on six standard fitness functions. Experimental results show that presented method has an acceptable performance (Yazdani et al. 2010).

4.5 CSA-AFSA

This hybrid method, a QoS multi cast routing algorithm based on clonal selection and artificial fish swarm algorithms (CSA-AFSA). The hybrid algorithms logically use the superiorities of both algorithms and try to overcome their inherent drawback. An improved initialization method is used to make sure each individual in initial population is a reasonable multi cast tree without loops. The simulation carried out with different network scale. The results have demonstrated the hybrid algorithm has the high speed of convergence and searching capability to solve QoS multi cast routing effectively (Huang et al. 2009).

4.6 CAFSA

According to the characteristics of artificial fish-swarm algorithm and chaos optimization algorithm, a kind of artificial fish-swarm algorithm with chaos is constructed by adding chaos to influence the update of the velocities of artificial fish, so that precocious phenomenon is suppressed, the convergence rate and the accuracy is improved. By testing two functions and NP hard problems of the Planar Location Problem, the experimental results show that the algorithm is an efficient global optimization algorithm for solving global optimization problem (Chen and Tian 2010).

In view of the defects of AFSA with slow convergence in the later period, low optimizing precision, and on some issues fall into local optimum easily. As well as the characteristics of chaos with periodicity and sensitivity to the initial value, add chaos to AFSA, guide the current optimized individual fish with Chaos iteration to further optimization. The main steps of Artificial Fish-Swarm Algorithm with Chaos are as follows:

Step1: Parameter setting, initialize the state of fish (population size is N). In the feasible region generates N artificial fish individual randomly, *visual* is the greatest perception distance of artificial fish, *Step* is the largest step, δ is crowed factor, n is the largest number of each artificial fish try to search food, c, d are chaotic mutation parameters.
Step 2: Initialization of bulletin board. Calculate the function value of each initial fish and compare the value, assign the best artificial fish to its bulletin board.
Step 3: Selecting behavior. Each artificial fish simulate the swarming and following behavior respectively, and select the best behavior to perform by comparing the function values, the default is searching food behavior.
Step 4: Chaotic mutation. Perform mutation to the current status of each fish depend on $Xinext = Xi + cti - d$, if the status out of the feasible region, then generate *Xinext* in feasible region randomly. Calculate $f(Xinsert)$, if $f\ (Xinext)$ is superior to $f(Xi)$, then, $Xi = Xinext$ Otherwise, do not update; set $ti = 4ti(1 - ti)$.
Step 5: Update bulletin board. According to the latest status of each fish, update bulletin board by comparing its fitness value, optimal state is *Xbest*.
Step 6: Perform chaotic mutation to the current optimal state of fish that on the Bulletin board. Perform chaotic mutation to the optimal state depend on $X_{inext} = X_i + cu - d$, if the status out of the feasible region, do not update. Calculated function values $f(Xcbest)$, if $f(Xcbest)$ superior to $f(Xbest)$, then, $Xbest = f\ (Xcbest)$ otherwise, do not update; set $u = 4u(1 - u)$.
Step 7: Check the termination condition. If meet, then jump out of iterative and output the optimal value; otherwise, turn to step 3.

Testing it with six-hump camel back function and Applying it to PLP demonstrates that the results that this hybrid algorithm has got better than AA has got. This algorithm can solves the constrained and unconstrained problem effectively.

4.7 CSAFSA

The idea of CSAFSA brings the CS mechanism into the operation flow of AFSA. On one hand it can enhance the global search capabilities and get out of the local optimum easily.

While on the other hand, it will not reduce the convergence speed and search accuracy at the same time. When all of the AF has completed one movement, evaluate the global best fish, and then use the chaos optimization algorithm to search around the position of best fish within a certain radius. If better, then replace the global best fish with this solution (Ma and Wang 2009). The execution of CSAFSA is as follows:

Step 1: Generate the initial fish swarm randomly in the search space;
Step 2: Initialize the value of bulletin board, calculate the current function value y of each AF, and assign the value of best fish to bulletin board;
Step 3: Simulate fish following behavior and fish swarming behavior respectively, and then select the behavior Results in better function value y, and the default behavior is fish preying;
Step 4: Check the function value y with the value of bulletin board. If better, then replace it;
Step 5: Perform chaos search near the current best AF. If better solution has been found, then replace the global best fish with this solution;
Step 6: Judge whether the preset maximum iteration number has achieved or a satisfactory optimum solution has obtained. If not satisfied, go to step 3. Otherwise go to step 7;
Step 7: Output the optimum solution.

4.8 ICAFSA

Having analyzed the deficiencies of AFSA and making use of the ergodicity and internal randomness of chaos optimization algorithm (COA), this propose further puts forward an improved chaotic artificial fish swarm algorithm (ICAFSA). In this improved algorithm, chaos optimization is first employed to initialize the position of individual artificial fish and then AFSA is applied to obtain the neighborhood of the global optimum solution. When there is no change or little change of the function values on bulletin board in successive iterations, chaotic mutation is then executed to help the artificial fish swarm gets rid of the local optimum. The findings of case study show the feasibility and effectiveness of the ICAFSA in the optimization operations of cascade hydropower stations (Guo et al. 2011).

Improved chaotic artificial fish swarm algorithm (ICAFSA) has coupled the characteristics of chaos search into the searching process of AFSA, in order to make up for the deficiency of being easily trapped into the local optimum of AFSA in the latter phase. The process of chaos mutation is as follows (Cheng et al. 2008):

(1) Let the k th generation of AF be $Z^k = (Z_1^k, Z_2^k, \ldots, Z_n^k)$ then map the variables to chaotic variable interval (0,1) respectively to form chaotic variable sequence Z^{k*}, $Z^{k*} = (Z_1^{k*}, Z_2^{k*}, \ldots, Z_n^{k*})$ the mapping equation is as follows:

$$Z_i^{k*} = \frac{Z_i^k - a_i}{b_i - a_i} \tag{19}$$

Among which, a_i and b_i are the minimum and maximum of the ith variable of Z^k respectively.
(2) The chaotic variable $Y_=(Y_1, Y_2, \ldots, Y_n)$ produced by Logistic Mapping Method is added to the variable Z^{k*} by certain probability, and then map the chaotic mutation individuals to interval (0, 1) as follows:

$$W_i^{k*} = Z_i^{k*} + \alpha.Y_i \tag{20}$$

Among which, Z^{k*} and W_i^{k*} are the chaotic values of the ith variable of Z^{k*} and W_i^{k*}, Y_i is the value of the ith variable of Y, and α is the annealing operation:

$$\alpha = 1 - \left|\frac{n-1}{n}\right|^k \tag{21}$$

(3) At last, chaotic mutation variable W_i^{k*} is mapped to the feasible region, and thus complete a mutative operation.

$$W_i^k = a_i + (b_i - a_i).W_i^{k*} \tag{22}$$

W_i^k is the chaotic value of the ith variables of W_i^k, $W^k = (W_1^k, W_2^k, \ldots, W_n^k)$.

4.9 AFSA-AL

This research presents an augmented Lagrangian methodology with a stochastic population based algorithm for solving nonlinear constrained global optimization problems. The method approximately solves a sequence of simple bound global optimization sub problems using a fish swarm intelligent algorithm. A stochastic convergence analysis of the fish swarm iterative process is included. Numerical results with a benchmark set of problems are shown, including a comparison with other stochastic-type algorithms (Rocha et al. 2010).

The algorithm AFSA based on the augmented Lagrangian (AFSA AL) is presented below.

Algorithm 1. AFS aL Algorithm

Given $\mu^+ > 0, 0 < \epsilon^* \ll 1, 0 < \alpha < 1, \gamma > 1, k_{\max}, 0 < \rho^- < \rho^+, \mu^1 \in [0, \mu^+]$;

Step 1. *Randomly generate* x^0 *in* Ω;

Step 2. *Compute* ρ^1 *using* (4), *and set k=1;*

Step 3. *Repeat*

$$\left\{\begin{array}{l}
For\ a\ certain\ tolerance\ \epsilon^k,\ find\ an\ appropriate\ minimizer\ x^k\ to\ the \\
subproblem\ (3)\ using\ the\ AFS\ Algorithm; \\
Update\ v^k\ using\ (5); \\
If\ k = 1\ or\ \left\|v^k\right\| \le \left\|v^{k-1}\right\|\ then \\
\quad \rho^{k+1} = \rho^k; \\
else \\
\quad if\ \left\|v^k\right\| \le \epsilon^k\ then \\
\quad\quad \rho^{k+1} = \max\left\{\rho^-, \frac{1}{\gamma}\rho^k\right\}; \\
\quad else \\
\quad\quad \rho^{k+1} = \min\left\{\rho^+, \gamma\rho^k\right\}; \\
\quad end\ if \\
end\ if \\
Update\ \mu_i^{k+1} = \min\left\{\max\left\{0, \mu_i^k + \rho^k g_i\left(x^k\right)\right\}, \mu^+\right\},\ i = 1, \ldots, p; \\
Set\ k = k + 1;
\end{array}\right.$$

$Until\ \left\|v^{k-1}\right\| \le \epsilon^*\ or\ k > k_{\max}$

The here in proposed technique for solving (3) uses a population-based algorithm that relies on swarm intelligence to converge towards the minimum value of the augmented Lagrangian function. This is the subject of the next section. Since the AFS algorithm provides a population of solutions, x^k is the best solution. They emphasize the importance of using x^k as one of the points of the population for the sub problem (3), at iteration $k + 1$. The remaining points of the population are randomly generated in the set Ω.

4.10 AHSN-AFSA

The adaptive hybrid sequences niche artificial fish swarm algorithm (AHSN-AFSA) is introduced, and study on how to apply the algorithm to solve the vehicle routing problem. The concept of ecological niche is also being introduced in order to overcome the shortcoming of traditional artificial fish swarm algorithm to obtain optimal solution. Simulation results show that the new algorithm has solved fast, stable performance and so on (Ma 2010).

4.11 TAFSA

In terms of some problems existing in the process of large case base retrieval, combining tabu search method and the advantages of artificial fish school algorithm, multilevel search strategy based on tabu artificial fish swarm algorithm. Tabu artificial fish swarm algorithm applies tabu table with a memory function to artificial fish swarm algorithm and uses different computing model in the similarity calculation according to properties of different types, effectively to avoid premature and blind search and other issues. Simulation results show that the algorithm outperforms other algorithms, it not only improves the retrieval accuracy and retrieval efficiency of the case based reasoning system, but also is characterized by requiring not much with the initial values and parameters, diversity search and overcoming the local maximum, better coordinate the overall and local search capabilities and provides an effective retrieval method to retrieve the case of large case base (Xu and Liu 2010).

4.12 AFSA-FCM

This method applies the artificial fish swarm algorithm (AFSA) to fuzzy clustering. An improved AFSA with adaptive Visual and adaptive step is proposed. AFSA enhances the performance of the fuzzy C-Means (FCM) algorithm. A computational experiment shows that AFSA improved FCM outperforms both the conventional FCM algorithm and the Genetic Algorithm (GA) improved FCM (He et al. 2009).

4.12.1 ASFA fuzzy clustering approach

A new fuzzy clustering algorithm based on FCM and AFSA is proposed here. The algorithm has the following steps:

Step 1(Determine parameter encoding)
$V = (v_1, v_2, \ldots, v_p, \ldots, v_c)$ (Represents the centroid of the clusters. It is considered to be one AF. v_p is the centroid of the p^{th} cluster ($1 \leq p \leq c$), where c is the number of clusters. V is a c*n dimension- vector.
Step 2 (Initialization)
Define the clusters number c, the population of AF N, fuzziness exponent m, termination criterion, visual distance of AF, step of AF, crowd factor and Trynumber. Determine maximum iteration time K for AFSA, set iteration counter k = 1; initialize the first AF population: $AF^K = \{V_1^K, V_2^K, \ldots, V_q^K, \ldots V_N^K\}$ where V_q^K.
Represents the position of the q^{th} AF at the K^{th} iteration.$1 \leq q \leq N$, N is the population of AF.
Step 3 (Global search)

a) According to V_q^K, calculate membership matrix $U_q^k = [u_{i,j}^k]_{c*n}$.

b) Go to step 4 when the result satisfies the termination criterion, otherwise, increment k (k: = k+1) and go back to step 3(a).

Step 4 (Local search)

a) Find the best individual AF: V_{best}^{k}
b) Calculate U^{K+1}
c) Update V^{k+1}
d) Stop iteration if the result satisfies termination criterion, or, increment k and return to step 4(b).

This algorithm is used to search for cluster centroid so that the objective function f is minimized. After each iteration, AFs swim to better locations. This enables convergence to the global optimum.

4.13 HAFSA

Based on particle swarm optimization (PSO) and artificial fish swarm algorithm (AFSA), a hybrid artificial fish swarm optimization algorithm is proposed. The novel method makes full use of the rapidly local convergent performance of PSO and the global convergent performance of AFSA, and then is used for solving ill-conditioned linear systems of equations. Finally, the numerical experiment results show that the hybrid artificial fish swarm optimization algorithm owns a good globally convergent performance with a faster convergent rate. It is a new way for solving ill-conditioned linear systems of equations (Xiu-xi et al. 2010).

4.14 NQAFSA

A novel Niche Quantum Artificial Fish Swarm Algorithm (NQAFSA) is proposed in this method to solve these problems. The quantum mechanism is introduced into the AFSA to increase the diversity of species. Artificial Fish (AF) are divided into several sub-swarms to form the niche and the restricted competition selection (RCS) strategy is used to maintain the niche. The performance of NQAFSA is validated by the experimental results (Zhu et al. 2010).

4.14.1 Niche artificial fish swarm algorithm based on quantum theory

Niching methods can find multiple solutions in multimodal domains, in contrast to AFSA that has been designed to locate only single optimal solution. A novel Niche Artificial Fish Swarm Algorithm based on Quantum theory called NQAFSA is proposed. Quantum mechanism is introduced into AFSA so as to enhance population variety and Niching method is introduced into AFSA in order to find multiple optimal solutions. The probability amplitudes of quantum bits are employed to encrypt the position of the AF. The quantum rotation gate is used to update the position of the AF in order to enable the AF to move and the quantum non-gate is employed to realize the mutation of the AF for speeding up the convergence.

The niche strategy is realized by the sub-swarm. The initial artificial fish swarm is split into smaller swarms as sub-swarm which is used to locate multiple solutions in multimodal function optimization problems. All the sub-swarm explores the search space in parallel way. The RCS strategy is employed to maintain the sub-swarm. The procedure of NQAFSA is shown as follows.

Step 1. Initialization, including the number of sub-swarms N, the number of AF in each sub-swarm *AF_total, AF_step, AF_visual, try_number*, mutation probability p_m and so on.
Step 2. A total of N sub-swarms are created and they are all randomly distributed in the search space. The positions of AFs are encoded by the probability amplitudes of quantum bits.
Step 3. Perform the solution space transformation for every AF in each sub-swarm and calculate fitness value of the AF, then the best AF in each sub-swarm will be included in the bulletin board of that sub-swarm.
Step 4. AF execute AF_Pray, AF_Swarm, AF_Follow, AF_Move and evaluate the results of the four behaviors. Then determine target position and change the position of the AF by quantum rotation gate.
Step 5. Perform the mutation operation. Generate a random number $rand_i$ between 0 and 1 for every AF, if $rand_i < p_m$, then execute mutation operation upon that AF.
Step 6. Perform the solution space transformation for every AF and calculate fitness value of the AF again, then update the bulletin board in each sub-swarm.
Step 7. The RCS strategy is executed to maintain the niche.
Step 8. If the stopping criterion is satisfied, then stop and output the result; else go to Step 4.

4.15 Hyperbolic penalty in the mutated artificial fish swarm algorithm

In this method the implementation of a population-based paradigm in the hyperbolic penalty function method to solve constrained global optimization problems are proposed. A mutated artificial fish swarm algorithm is used to solve the bound constrained sub problems. A simple tuning of the penalty parameters and three schemata for the implementation of an intensification local search procedure are introduced to promote convergence and improve the global solution. They may conclude that the proposed algorithm with an HJ strengthening strategy outside the outer cycle provides promising results when solving engineering design problems (Rocha et al. 2011).

4.16 Parallel fish swarm algorithm

With the development of Graphics Processing Unit (GPU) and the Compute Unified Device Architecture (CUDA) platform, researchers shift their attentions to general-purpose computing applications with GPU. In this method, they present a novel parallel approach to run artificial fish swarm algorithm (AFSA) on GPU. Experiments are conducted by running AFSA both on GPU and CPU respectively to optimize four benchmark test functions. With the same optimization performance, the running speed of the AFSA based on GPU (GPU-AFSA) can be as 30 time fast as that of the AFSA based on CPU (CPU-AFSA). As far as they know; this is the first implementation of AFSA on GPU (Hu et al. 2011).

4.17 QAFSA

In order to improve the global search ability and the convergence speed of the Artificial Fish Swarm Algorithm (AFSA), a novel Quantum Artificial Fish Swarm Algorithm (QAFSA) which is based on the concepts and principles of quantum computing, such as the quantum bit and quantum gate is proposed in this method. The position of the Artificial Fish (AF) is encoded by the angle in $[0, 2\pi]$ based on the qubit's polar coordinate representation in the 2-dimension Hilbert space. The quantum rotation gate is used to update the position of the AF in order to enable the AF to move and the quantum non-gate is employed to understand the mutation of the AF for the purpose of speeding up the convergence. Quick convergence and good global search capacity characterize the performance of QAFSA. The experimental results prove that the performance of QAFSA is meaningfully improved compared with that of standard AFSA (Zhu and Jiang 2010).

4.18 SA-AFSA

This method presents a novel stochastic approach called the simulated annealing-artificial fish swarm algorithm (SA-AFSA) for solving some multimodal problems. The proposed algorithm incorporates the simulated annealing (SA) into artificial fish swarm algorithm (AFSA) to improve the performance of the AFSA. The hybrid algorithm has the following features: the hybrid algorithm maintains (1) the strong local searching ability of the SA and (2) the swarm intelligence of AFSA. The experimental results shows that in all the test cases, the SA-AFSA can obtain much better optimization precision and the convergence speed compared with AFSA (Jiang and Cheng 2010).

5 Application AFSA

The AFSA is a new and modern algorithm for optimization purposes. In short term it has succeeded to get its place among other optimization methods. Many researchers have applied this algorithm in different applications. In this section, its different applications are described.

5.1 Control

5.1.1 AFSA-FLC

This method provides an overview on the Artificial Fish Swarm Algorithm (AFSA) for the automated design and optimization of fuzzy logic controller. A new optimization method for fuzzy logic controller design is proposed. The membership functions of input and output variables are defined by six parameters, which are adjusted to maximize the performance of the controller by using AFSA. This method can improve the ability of search and convergence of algorithm. Simulation experiment on water level controller is discussed by using above method. The simulation results show that fuzzy logic controller based on AFSA avoids premature effectively and prove its feasibility (Tian et al. 2009b).

5.1.2 Self adaptive control algorithm of the artificial fish formation

With the deep study of swarm intelligence, biologists found that fish swarm changes in formation progressively in time during their movement. This forming change leads to a better and more effective access to evade predator and chance to capture food, so that the group's overall performance is improved. The architecture of artificial fish formation is established based on the behavioral model of artificial fish swarm. The mechanism of formation change is analyzed. A self-adaptive control algorithm of formation is proposed in this method. The parameters optimized PSO algorithm is used to simulate the process of keeping its balance during the formation change. Thus, the problem on relative bad adaptability and large systematic traffic in existent algorithms of formation is resolved (Ban et al. 2009).

5.1.3 AFSA for multi robot task scheduling

The main aim of this study is managing robot tasks to minimize the deviation between the resource requirements and stated desirable levels. Some improved adaptive methods about step length are proposed in the Artificial Fish Swarm Algorithm (AFSA). In this study resource leveling methods are used to solve task scheduling problems in autonomic multi robot group. Robots are considered as resources. The experimental results show that proposed methods have better performances such as good and fast global convergence, strong robustness, insensitive to initial values, simplicity of implementation (Tian and Liu 2009).

5.1.4 AFSA in UCAV path planning

The path planning method based on artificial fish school algorithm (AFSA) was proposed to solve unmanned combat aerial vehicle (UCA V) path planning problem under the 2-D radar threats environment. According to the path planning requirements, the threat detection and artificial fish coding method were designed in detail. Besides, the method of perceiving threats was applied for advancing the feasibility of the path. A comparison of the results was made by WPSO, CFPSO and AFSA, which showed that the method they proposed in this paper was effective. AFSA was much more suitable for solving this kind of problem (Ma and Lei 2010).

5.1.5 AFSA for fault diagnosis in mine hoist

It has been presented an intelligent methodology for diagnosing initial faults in mine hoist. As Probabilistic Causal-effect Model-Based diagnosis is an active branch of Artificial Intelligent, the feasibility of using probabilistic causal-effect model is studied and it is applied in artificial fish-swarm algorithm (AFSA) to classify the defects of mine hoist. In probabilistic causal-effect model, they employed probability function to nonlinearly map the data into a feature space, and with it, fault diagnosis is simplified into optimization problem from the original complex feature set. And an improved distance evaluation method is proposed to identify different abnormal cases. The proposed approach is applied to fault diagnosis of friction hoist with many steel ropes, and testing results show that the proposed approach can reliably recognize different fault categories.

Moreover, the effectiveness of the method of mapping hitting sets problem to 0/1 integer programming problem is also exhibited by the testing results. It can get 95–100 % minimal diagnosis with cardinal number of fault sign sets greater than 20 (Chu-Jiao and Chu-Jiao 2010).

5.1.6 CAFAC

Efficient identification and control algorithms are required, when active vibration suppression techniques are developed for industrial machines. A new actuator for reducing rotor vibrations in electrical machines is investigated. Model-based control is needed in designing the algorithm for voltage input, and therefore proper models for the actuator must be available. In addition to the traditional forecasting error method a new knowledge-based artificial fish-swarm optimization algorithm (AFA) with crossover, CAFAC, is proposed to identify the parameters in the new model. Then, in order to obtain a fast convergence of the algorithm in the case of a 30 kW two-pole squirrel cage induction motor, they combine the CAFAC and particle swarm optimization (PSO) to identify parameters of the machine to construct a linear time-invariant (LTI) state-space model. Besides that, the prediction error method (PEM) is also employed to identify the induction motor to produce a black box model with correspondence to input-output measurements (Wu et al. 2011).

5.1.7 MOAFSA

An approach using AFSA to solve the multiobjective optimization problem is proposed. In this algorithm, the idea of Pareto dominance is used to evaluate the pros and cons of artificial fish (AF). Artificial fish swarm search the solution space in parallel and External Record Set is used to save the found Pareto optimal solutions. The simulation results of 4 benchmark test functions demonstrate the effectiveness of the proposed algorithm (Jiang and Jiang 2011).

5.1.8 PID controller parameters based on an improved AFSA

The artificial fish swarm algorithm is a new kind of optimizing method based on the model of autonomic animals. After analyzing the disadvantages of AFSA, an improved artificial fish swarm algorithm is displayed. According to the ergodicity and stochastic of chaos, the basic AFSA is combined with chaos in order to initialize the fish school. The improvement of the swarming behavior increased the accuracy of the algorithm. In the behavior of preying, the strategy of dynamically adjusting the parameter of step is presented in order to improve the convergence rate of the algorithm. This improved AFSA is applied in the optimization of the of PID controller parameters. The simulation results show that this improved AFSA algorithm is effective and better than the basic AFSA algorithm (Luo et al. 2010).

5.1.9 Optimum steelmaking charge plan using AFSA

An optimum furnace charge plan model for steelmaking continuous casting planning and scheduling is displayed an artificial fish swarm optimization (AFSO) algorithm is used to solve the optimum charge plan problem. The computation with useful data shows that the model and the solving method are vey efficient (Xue et al. 2004).

5.1.10 AFSA for the target area on simulation robots

In this research, they used an improved algorithm of artificial fish, and did the optimization in setting the border in the simulation platform, especially in the field of choosing ways of the robots; they used the multi-threshold to reduce the uncontrollable actions when robots are in the game. And this method gives them an acceptable way to solve the issue (Feng et al. 2010).

5.2 Image processing

5.2.1 AFSA-Kmeans

Data clustering has been used in different fields such as machine learning, data mining, wireless sensory networks and pattern recognition. One of the most well-known clustering methods is K-means which has been used effectively in many of clustering problems. But this algorithm has problems such as convergence in local minimum and sensitivity to initial points. A hybrid clustering method, based on artificial fish swarm optimization (AFSO) and K-means so called KAFSO is proposed. In this proposed algorithm, high ability of AFSO in global searching as well as high ability of K-means in local searching has been used cooperatively. The proposed method has been tested on eight collections of standard data and its efficiency has been compared with standard methods PSO, Kmeans, K-PSO and AFSO. Experimental results showed that proposed approach has suitable and acceptable efficacy in data clustering (Neshat et al. 2011).

5.2.2 HA-FC

In CBR system, the case base is becoming increasingly larger with the incremental learning which results in the decrease of case retrieval efficiency and its bad performance. Aiming at such weakness of CBR system, a novel case retrieval method based on hybrid ant-fish clustering algorithm (HA-FC). At beginning of algorithm, they get rough cluster sets utilizing the advantage of Artificial Fish-school Algorithm which is insensitive to initial value and has high speed of searching optimizing. Then they used ant Colony Optimization introduced the concept of Crowded Degree to avoid convergence too early and improve the ability of searching optimizing. Finally, apply this algorithm to case retrieval in order to reduce searching time and improve searching accuracy. The results of simulation demonstrate the effectiveness of this algorithm (Huang and Wang 2010).

5.2.3 A clustering algorithm based on artificial fish school

For avoiding the dependence of the validity of clustering on the space distribution of high dimensional samples of Fuzzy C2Means, a dynamic fuzzy clustering method based on artificial fish swarm algorithm was proposed with introducing a fuzzy equivalence matrix to the similar degree among samples, the high dimensional sample s were mapped to two dimensional planes. Then the Euclidean distance of the samples was approximated to the fuzzy equivalence matrix gradually by using artificial fish warm algorithm to optimize the coordinate values. Finally, the fuzzy clustering was obtained. The proposed method, not only avoided the dependence of the validity of clustering on the space distribution of high dimensional samples, but also raised the clustering efficiency. Experiment results show that it is an efficient clustering algorithm (Xiao 2010).

For clusters of individual fish behavior in the initial state for the Xi, any exploration of a state Xj, calculate dij and dij = || Xi − Xj ||, if j's position is not too crowded place i move to j, otherwise implementation of the foraging behavior and foraging behavior of the state is a random choice, so difficult in the short time between the individual fish to find categories. If the initial heuristic is given when the amount of information that can further enhance the convergence speed.

The specific steps the algorithm Based cluster analysis of the data set is X = (Xi = (xi1, xi2,..., xin), i = 1, 2, ..., n), concrete steps are as follows:

(*a*) n 0 (n is number of cycles), given the variables in fish (bisual, step,) the initial value and the current state of the AF_X.
(*b*) First for fast classification, the classification results calculated according to the cluster center Zj (j = 1, 2 ..., K).

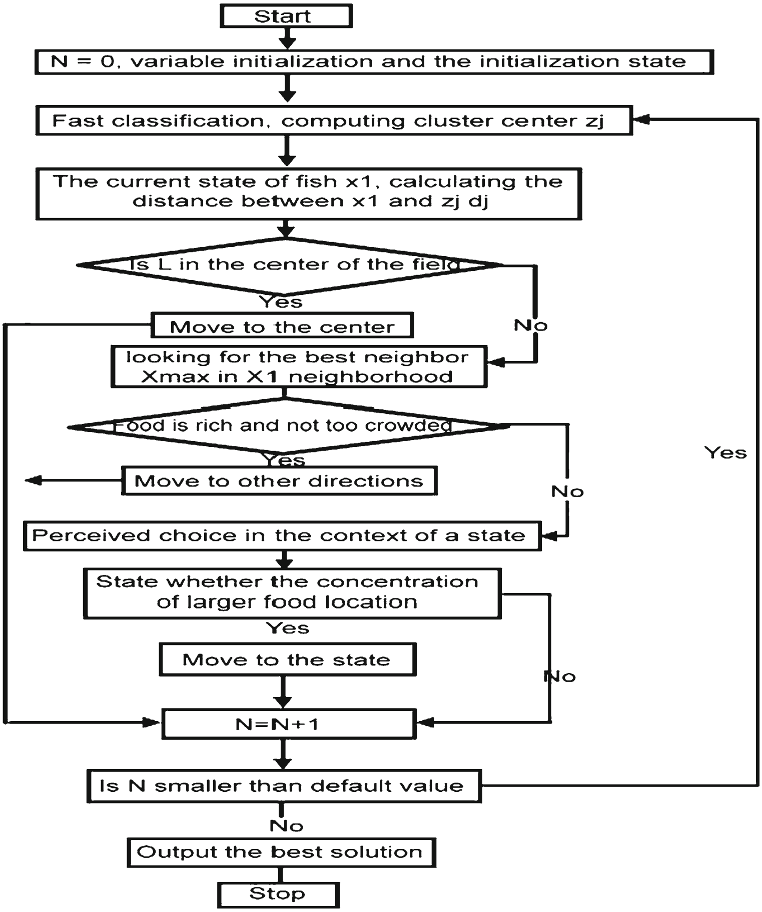

Fig. 6 Clustering algorithm based on artificial fish flow

(*c*) the current status of individual fish, Xi, calculated with center Zj (j = 1, 2 …, K).'s Distance, if its not too crowded neighborhood of the center is moving toward the center.
(*d*) Otherwise, the best neighborhood to find Xi neighbor Xmax. If the food is rich in not too crowded to its direction.
(*e*) In two steps do not meet their perception in the context of the election of a state, if the location of the food concentration is high then its direction.
(*f*) n n +1, if n is greater than the number required to stop operation, output the best solution. Otherwise transfer step (2) to continue (Fig. 6).

5.2.4 Image reconstruction algorithm based on AFS for ECTS

According to the fundamental principles of electrical capacitance tomography (ECT), a new ECT algorithm optimized radial basis function (RBF) neural network algorithm, which is based on AFSA, is proposed against the "soft field" effects and ill-conditioning problems in ECT technology. After giving the mathematic model of the algorithm, this research also applies the AFSA to the training process of neural networks to compare with the traditional neural network algorithm. Finally, a conclusion that with little error, high quality and fast convergence rate, etc. The ECT image reconstruction algorithm which is based on AFSA and the optimized RBF neural networks providing a new way for the ECT image reconstruction algorithm is reached (Deyun et al. 2011).

5.2.5 Artificial fish-fuzzy c-means clustering algorithm

By analyzing advantages and disadvantages of fuzzy C-means clustering algorithm, a method of image segmentation based on fuzzy C-means clustering algorithm and artificial fish swarm algorithm is proposed. The image is segmented in terms of the values of the membership of pixels, AFSA is introduced into fuzzy C-means clustering algorithm, and through the behavior of prey, follow, swarm of artificial fish, the optimized clustering center could be selected adaptively, then the values of the membership of pixels available with fuzzy C-means clustering algorithm, and the image segmentation is completed. The experimental results show the efficiency and feasibility (XiaoLi et al. 2010).

5.2.6 IAFSC

An improved artificial fish swarm algorithm (IAFSA) is proposed, and its complexity is much less than the original algorithm (AFSA) because of a new proposed fish behavior. Based on IAFSA, two novel algorithms for data clustering are presented. One is the improved artificial fish swarm clustering (IAFSC) algorithm, the other is a hybrid fuzzy clustering algorithm that combines the Fuzzy C-means (FCM) into the IAFSA. The performance of the proposed algorithms is compared with that of the PSO, K-means and FCM, respectively on Iris testing data. Simulation results show that the performance of the proposed algorithms is much better than that of the PSO, K-means and FCM. And the proposed hybrid fuzzy clustering algorithm evades the FCM's weakness such as initialization value problem and local minimum problem (Cheng et al. 2009).

5.2.7 IAFSA-segmentation

An improved artificial fish swarm algorithm is proposed to search the optimal parameter combination in this method. It is concerned with fuzzy entropy definition used for image segmentation. The key problem associated with this method is to find the optimal parameter combination of membership function so that an image can be changed into fuzzy domain with maximum fuzzy entropy. Then, they compare the improved artificial fish swarm algorithm with other artificial intelligence models. The experiment indicates that the proposed method is completely effective and present everywhere (Tian et al. 2009a).

5.2.8 CQAFSA

Color quantization (CQ) is one of the important techniques in image compression, graphic and image processing. Most of quantization methods are based on clustering algorithms. Data clustering is a non-supervised classification technique and belongs to NP-hard problems. One of the methods for solving NP-hard problems is applying swarm intelligence algorithms. In this research, a modified AFSA is proposed for doing CQ. In the proposed algorithm, to improve the efficiency and delete AFSA disadvantages, some modifications are done on behaviors, parameters and the algorithm procedure. The proposed algorithm along with other multiple known algorithms has been used on some famous images for doing CQ. Experimental results comparison shows that the proposed algorithm has acceptable efficiency (Yazdani et al. 2011).

5.3 Network

5.3.1 WSN-AFSA

Wireless sensor networks (WSN) will enable the reliable monitoring of a variety environment for both civil and military applications. These networks require robust wireless communication protocols for the goal of equilibration the load and prolonging the network lifetime. In this method, they propose a novel hierarchical routing protocol based on artificial fish swarm optimization (AFSO). Utilizes AFSO algorithm in cluster formation phase, its main object is to solve the NP-hard problem of finding k optimal clusters according to the given rules. The performance of the novel protocol is compared with the famous cluster-based protocol LEACH and LEACH-C. As the experiment results shown, the protocol can not only improve system lifetime but also impede the networks form seriously energy consumption (Song et al. 2010).

5.3.2 The hybrid algorithm based on fish and particle swarm algorithm

The coverage problem is one basic problem in the wireless sensor networks (WSNs). In one limited region, how to logically arrange the sensor nodes to obtain the best coverage is the key to improve the performance of the whole networks. a hybrid algorithm which is based on the fish swarm algorithm and particle swarm optimization in the limited WSNs region. The new algorithm has the well global search capacity of the fish swarm algorithm and the rapidly search ability of the particle swarm optimization. The simulation results show that the hybrid algorithm can efficiently optimize the nodes' deployment of the sensor networks to improve the coverage of the whole networks (Bin et al. 2011).

5.3.3 AFSA in intrusion detections

A method of optimization and simplification to network feature using Artificial Fish-swarm Algorithm in intrusion discovery is proposed in this method for solving problems of more features and slower computing speed. This method founded mathematic model aimed at obtaining higher detection rate and lower false positive rate, and obtaining optimal feature attributes through iterative method by using an optimization policy on the basis of "PREY, SWARM and FOLLOW" operators. 41 features are optimized and simplified by adopting this method. 31 % feature attributes are obtained which can totally reflect intrusion feature. The experimental results indicate that using feature attributes after optimization and simplification can shorten 40 % work time in intrusion detection (Tao et al. 2009).

5.3.4 QoS-AFSA

Bandwidth-delay-constrained multicast routing problem is an NP-complete problem. a QoS multicast routing algorithm based on Artificial Fish Swarm optimization. Meeting with the Bandwidth-delay constrained, the proposed algorithm can search the least-cost multicast routing tree rapidly. Simulation results show that this algorithm has high reliability and good execution of global optimization, and suit for real-time, high-speed multimedia transmission network (LIU et al. 2009).

5.3.5 IMAFSA

The hybrid artificial fish swarm optimization algorithm based on mutation operator and simulated annealing algorithm (MAFSA) is studied and improved. The mutation operator was improved and a method for experimental determining of mutation probability was presented in improved MAFSA (IMAFSA). Besides, economic and security objective function is also applied to improve the model of reactive power optimization of distribution network. The result obtained from simulated calculation in real distribution network shows that the IMAFSA applied in reactive power optimization of distribution network is reasonable and achievable (Yuan et al. 2010).

5.3.6 IAFSO-IECBP

IEC three-ratio is an effective method for transformer fault diagnosis in the dissolved gas analysis (DGA). Considering the characteristic of three-ratio boundary is too absolute, fuzzy knowledge is utilized to preprocess. As the same time, for overcoming the lack of the back propagation (BP), an improved artificial fish swarm optimization (IAFSO) algorithm is used to optimize the weight and threshold of the BP. The global searching ability of the IAFSO approach is utilized to find the global optimization solution. It can overcome the slower convergence velocity and easily getting into local extremum of the BP neural network. So, aiming at the shortcoming of BP neural network and three ratios, blurring the boundary of the gas ratio and the IAFSO algorithm is introduced to optimize the BP network. Then the IAFSO-IECBP method is proposed. Experimental results indicate that the proposed algorithm in this method that both convergence velocity and accuracy are all improved to some extent. Justness and validity of this proposed method has also confirmed for transformer fault diagnosis (Yu et al. 2010).

5.4 Neural network

5.4.1 NNC-AFSA

As a novel simulated evolutionary computation method, Artificial Fish Swarm Algorithm (AFSA) shows many promising characters. The use of AFSA as a new tool which sets up a neural network (NN), adjusts its parameters, and performs feature reduction, all simultaneously. In the optimization process, all features and hidden units are encrypted into a real-valued artificial fish (AF), and give out the method of designing fitness function. The experimental results on several public domain data sets from UCI show that this algorithm can obtain an optimal NN with fewer input features and hidden units, and perform almost as good as even better than an original complex NN with entire input features. And also indicate that optimizing a network classifier for a specific task has the potential to produce a simple classifier with low classification error and good generalization ability (Zhang et al. 2006).

5.4.2 Forecasting stock indices using RBFNN by AFSA

Stock index forecasting is a hot issue in the financial stage. As the movements of stock indices are nonlinear and subject to many internal and external factors, they pose a great challenge to researchers who try to predict them. they select a radial basis function neural network

(RBFNN) to train data and forecast the stock indices of the Shanghai Stock Exchange. They introduce the artificial fish swarm algorithm (AFSA) to optimize RBF. To increase forecasting efficiency, a K-means clustering algorithm is optimized by AFSA in the learning process of RBF. To verify the usefulness of this algorithm, they compared the forecasting results of RBF optimized by AFSA, genetic algorithms (GA) and particle swarm optimization (PSO), as well as predicting results of ARIMA, BP and support vector machine (SVM). Their experiment indicates that RBF optimized by AFSA is an easy-to-use algorithm with considerable accuracy. Of all the combinations they tried in this method, BIAS6 + MA5 + ASY4 was the optimum group with the least errors (Shen et al. 2011).

5.4.3 Freight prediction based on BPNN improved by CAFSA

Back propagation (BP) neural network has widely application because of its ability of self-studying, self-adapting and generalization. But there are some inherent defaults, such as low convergence speed, local extremes and so on. Artificial fish swarm algorithm (AFSA) is an up-to-date proposed optimal strategy, which possesses good ability to avoid the local extremum and obtain the global extremum. In order to improve the search efficiency of AFSA, Chaos system is introduced. A quantitative forecast method based on the BP network improved by Chaos artificial fish-swarm algorithm is proposed. The model is trained with the freight data of a city and then used to forecast the freight. Compared the simulated results with BP network and BP network improved by other algorithm, it concludes that CAFSA-BPN has smaller error in forecasting. And it indicates that CAFSA has the capability of fast learning the weight of network and globally search, and the training speed of the improved BP network is greatly raised (Huang and Lin 2008).

5.4.4 RF-AFSA for short time forecast of stock indices

The movement of stock index is difficult to prophesy for it is non-linear and subject too many inside and outside factors. Researchers in this field have tried many methods, SVM and ANN, for example, and have achieved good results. In this method, they select radial basis functions neural network (RBFNN) to train data and predict the stock index in Shanghai Stock Exchanges. In order to solve the problem of slow convergence and low accuracy, and to ensure better forecasting result, they introduce AFSA to optimize RBF, principally in parameter selection. Empirical tests indicate that RBF neural network optimized by AFSA can have ideal result in short-term forecast of stock indices (Dongxiao and WeiShen 2010).

5.4.5 Time series forecasting on novel SVM using AFSA

Time series analysis is an important and complex problem in machine learning. Support vector machine (SVM) has lately appeared as a powerful technique for solving problems in regression, but its performance principally depends on the parameters selection of it. Parameters selection for SVM is very complex in nature and quite hard to solve by conventional optimization techniques, which constrains its application to some degree. AFSA is proposed to choose the parameters of least squares support vector machine (LS-SVM) automatically in time series forecasting. This method has been applied in a real Electricity Load Forecasting, the results exhibit that the proposed approach has a better performance and is also more accurate and effective than LS-SVM based on particle swarm optimization (Chen et al. 2008).

5.5 Scheduling

5.5.1 IAFSA-RL

The planning and execution of power plant project have the characters of "within long period, large Resource devotion and resource imbalance". Project resource distribution is not an ideal state, but is "multi peak" and "multi-valley". This imbalance increases investment risks, which may cause waste of resources. Therefore, it is pressingly necessary to make a reasonable adjustment in the network planning process in order to achieve a balanced allocation of resources and to solve the problems. Resource leveling can be classified into a mathematical model with a class of nonlinear programming, but there are imitations in study. In large scale networks, the CPU time for solving such problems increases exponentially with the rising of the number of network nodes. As to different network structures and different parameters, the affect on resources leveling is not the same. Network parameters can be considered as AF. The improved AFSA algorithm considers about the optimal individual, and the weighted processing identifies Global optimal program. It keeps away the process of optimization in a "local optimization, and global nongifted" result. So, the application of AFSA in resources leveling can extend profound manifestation of the superiority of the algorithm (Tian and Tian 2009).

5.5.2 Efficient job scheduling in grid computing with MAFSA

Job scheduling is known to be NP-complete, therefore the use of non-heuristics is the in reality approach in order to cope in practice with its difficulty. A modified artificial fish swarm algorithm (MAFSA) for job scheduling. The basic idea of AFSA is to imitate the fish behaviors such as preying, swarming, and following with local search of fish individual for reaching the global optimum. The results indicate that this method is insensitive to initial values, has a strong robustness and has the faster convergence speed and better estimation accuracy than the estimation method by genetic algorithm (GA) and simulated annealing (SA) (Farzi 2009).

5.5.3 Multi-robot task allocation and scheduling based on FSA

The problem of multi robot task allocation and scheduling is to assign more relative tasks to less relative robots and to scheme task processing sequence so as to minimize the processing time of these tasks. The key of this problem is to allocate correct quantity of tasks for each robot and schedule the optimal task sequence for each robot. So that minimize the processing time for robots, an optimized multiple robots task allocation and scheduling approach based on fish swarm algorithm is proposed. In this approach, the optimized task sequence is first schemed using fish swarm algorithm on the assumption that all the tasks are processed by one robot. Then, according to the number of the robots, the task sequence has been randomly divided into several task segments that will be appointed to robots. At last, the task numbers of each task segments are averaged according to the time each robot used, therefore proper quantity of tasks is allocated to each robot and the optimized task allocation scheme is got. To validate the efficiency of the proposed approach, experiments and simulation have been made. The results show that the proposed approach can scheme optimized multi robots task allocation and scheduling scheme (Zheng and Li 2010).

5.5.4 Scheduling arrival aircrafts on multi-runway based on an IAFSA

The aircraft landing scheduling (ALS) problem is a typical NP-hard optimization problem. Based on an improved artificial fish swarm algorithm (IAFSA), the problem of scheduling reaching aircrafts at an airport with multi-runway is studied. A mutation operator is introduced to the artificial fish swarm algorithm. The sequence problem of landing aircraft is solved, and the simulation result shows that the IAFSA of ALS is better than FCFS which can decrease the total delay time by 24.1 %. This method can obtain a satisfactory solution which can provide real-time support for automatic air traffic management (Bing and Wen 2010).

5.6 Signal processing

5.6.1 A weak signal detection method based on AFSO matching pursuit

To detect weak signals is difficult in signal processing and is very important in many areas such as non-destructive evaluation (NDE), radar etc. Sparse signal disintegration from over complete dictionaries is the most recent technique in the signal processing community. This technique is utilized to cope with ultrasonic weak flaw detection problem. But its calculation is enormous (NP problem). A new improved matching chase algorithm is proposed. The mathematical model of searching algorithms based on artificial fish swarm is established; the artificial fish swarm with the advantages of distributed parallel searching ability, strong robustness, good global astringency, and insensitive preferences are employed to search the best matching atoms. It can reduce complexity of sparse decomposition and space of memory. Experimental results shows that the amplitude, frequency and initial phase parameters of ultrasonic signal blurred by strong noise can be estimated according to the proposed algorithm and the expected weak signal can be then rebuilt. When this method is used in the ultrasonic flaw detection, compared with the wavelet entropy and wavelet transform, the results show that the signal quality and performance parameters are improved obviously (Ai-ling et al. 2009).

5.6.2 Wavelet threshold optimization with AFSA

This algorithm can be used to the solution of global optimization problems and is an application prototype of swarm intelligent optimization problem. It uses the animal bottom behavior process, and finds the global optimum through the individual's local optimization. Signal processing includes many optimization problems, and they can decrease the processor (storage resource) or enhance the effect of signal processing by optimization. Here they acquire the optimal wavelet de-noising threshold using the new optimization algorithm-AFSA (Jiang and Yuan 2005).

6 Conclusion

The AFSA algorithm is one of the most appropriate methods for swarm intelligence optimization. This algorithm is capable of solving the problems by inspiration from the en masse movement of fishes. Fishes show different behaviors including seeking for food, following other fishes, protecting the group against threats and stochastic search. These behaviors have been employed in the AFSA and an acceptable result has been obtained. This algorithm shows more intelligent behavior and obtains more optimized results compared with other swarm intelligence algorithms. Of course, this algorithm has some disadvantages like falling in local optimum points, advanced convergence and time consuming. This algorithm is one of the best approaches of the Swarm Intelligence method with considerable advantages like high convergence speed, flexibility, error tolerance and high accuracy. This paper review the AFSA algorithm, its evolution stages from the start point up to now, improvements and applications in various fields like optimization, control, image processing, data mining, improving neural networks, networks, scheduling, and signal processing and so on. Also, various methods combining the AFSA with other optimization methods like PSO, Fuzzy Logic, Cellular Learning Automata or intelligent search methods like Tabu search, Simulated Annealing, Chaos Search etc. This algorithm has been widely used in short time and we hope the researchers can improve it more.

References

Ai-ling Q, Hong-wei M, Tao L (2009) A weak signal detection method based on artificial fish swarm optimized matching pursuit. In: World congress on computer science and information engineering, pp 185–189

Ban X, Yang Y, Ning S, Lv X, Qin J (2009) A self-adaptive control algorithm of the artificial fish formation. FUZZ-IEEE, Korea, 1903–1908, August 20–24

Bin Z, Jianlin M, Haiping L (2011) A hybrid algorithm for sensing coverage problem in wireless sensor networks. IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems, March 20–23, Kunming, China, pp 162–165

Bing D, Wen D (2010) Scheduling arrival aircrafts on multi-runway based on an improved artificial fish swarm algorithm. In: International conference on computational and information sciences, pp 499–502

Chen Z, Tian X (2010) Artificial fish-swarm algorithm with chaos and its application. In: IEEE second international workshop on education technology and computer science, pp 226–229

Chen X, Wang J, Sun D, Liang J (2008) Time series forecasting based on novel support vector machine using artificial fish swarm algorithm. In: IEEE fourth international conference on natural computation

Cheng C, Wang W, Xu D, Chau KW (2008) Optimizing hydropower reservoir operation using hybrid genetic algorithm and chaos. Water Resour Manage 22(7):895–909

Cheng YM, Jiang MY, Yuan DF (2009) Novel clustering algorithms based on improved artificial fish swarm algorithm. In: Proceedings of the 6th international conference on fuzzy systems and knowledge discovery (FSKD'09), 14–16 August, Tianjin, China, pp 141–145

Chu-Jiao W, Chu-Jiao W (2010) Application of probabilistic causal-effect model based artificial fish-swarm algorithm for fault diagnosis in mine hoist. J Softw 5(5):474–481

Deyun C, Lei S, Zhen Z, Xiaoyang Y (2011) An image reconstruction algorithm based on artificial fish-swarm for electrical capacitance tomography system. In: IEEE the 6th international forum on strategic technology, August 22–24, pp 1190–1194

Dongxiao N, WeiShen (2010) RBF and artificial fish swarm algorithm for short term forecast of stock indices. In: Second international conference on communication systems, networks and applications, pp 139–142

Farzi S (2009) Efficient job scheduling in grid computing with modified artificial fish swarm algorithm. Int J Comput Theory Eng 1(1):13–18

Feng X, Yin1 J, Xu M, Zhao X, Wu B (2010) The algorithm optimization on artificial fish-swarm for the target area on simulation robots. In: IEEE 2nd international conference on signal processing systems (ICSPS), pp 87–89

Fernandes Edite MGP, Martins Tiago FMC, Rocha Ana Maria AC (2009) Fish swarm intelligent algorithm for bound constrained global optimization. In: Proceedings of the international conference on computational and mathematical methods in science and engineering, CMMSE, 30 June, 1–3 July

Gao XZ, Wu Y, Zenger K, Huang X (2010) A knowledge-based artificial fish-swarm algorithm. In: 13th IEEE international conference on computational science and engineering

Guo W, Fang G, Huang X (2011) An improved chaotic artificial fish swarm algorithm and its application in optimizing cascade hydropower stations. In: IEEE international conference on business management and electronic information (BMEI), pp 217–220

He S, Belacel N, Hamam H, Bouslimani Y (2009) Fuzzy clustering with improved artificial fish swarm algorithm. In: International joint conference on computational sciences and optimization, pp 317–321

Huadong C, Shuzong W, Jingxi L, Yunfan L (2007) A hybrid of artificial fish swarm algorithm and particle swarm optimization for feedforward neural network training. In: IEEE advanced intelligence system research, October

Huang Y, Lin Y (2008) Freight prediction based on BP neural network improved by chaos artificial fish-swarm algorithm. In: International conference on computer science and software engineering, pp 1287–1290

Huang Z-J, Wang B-Q (2010) A novel swarm clustering algorithm and its application for CBR retrieval. In: 2nd International conference on information engineering and computer science (ICIECS), pp 1–5

Huang R, Tawafik H, Nagar A, Abbas G (2009) A novel hybrid QoS multicast routing based on clonal selection and artificial fish swarm algorithm. In: IEEE second international conference on development in system engineering, pp 47–52

Hu Y, Yu B, Ma J, Chen T (2011) Parallel fish swarm algorithm based on GPU acceleration. In: IEEE 3rd international workshop on intelligent systems and applications (ISA), 28–29 May

Jiang M, Cheng Y (2010) Simulated annealing artificial fish swarm algorithm. In: IEEE 8th world congress on intelligent control and automation, July 6–9, Jinan, China

Jiang M, Jiang M (2011) Multiobjective optimization by artificial fish swarm algorithm. In: IEEE international conference on computer science and automation engineering (CSAE), pp 506–511

Jiang MY, Yuan DF (2005) Wavelet threshold optimization with artificial fish swarm algorithm. In: Proceedings of the IEEE international conference on neural networks and brain, ICNN&B Oct.'05, pp 569–572

Jiang M, Wang Y, Rubio F, Yuan D (2007) Spread spectrum code estimation by artificial fish swarm algorithm. In: IEEE international symposium on intelligent signal processing (WISP)

Jiang M, Yuan D, Cheng Y (2009) Improved Artificial Fish Swarm Algorithm. In: IEEE fifth international conference on natural computation

Li XL (2003) A new intelligent optimization-artificial fish swarm algorithm. PhD thesis, Zhejiang University, China, June

Li LX, Shao ZJ, Qian JX (2002) An optimizing method based on autonomous animals: fish-swarm algorithm. Syst Eng Theory Practice 22(11):32–38

Liu C-b, Luo Z-p, Wang H-j, Yu X-q, Liu L-h (2009) QoS multicast routing problem based on artificial fish-swarm algorithm. In: IEEE first international workshop on education technology and computer science, pp 814–817

Luo Y, Wei W, Wang SX (2010) Optimization of PID controller parameters based on an improved artificial fish swarm algorithm. In: IEEE third international workshop on advanced computational intelligence, August 25–27, Suzhou, Jiangsu, China, pp 328–332

Ma X (2010) Application of adaptive hybrid sequences Niche artificial fish swarm algorithm in vehicle routing problem. IEEE 2nd Int Conf Future Comput Commun 1:654–658

Ma Q, Lei X (2010) Application of artificial fish school algorithm in UCA V path planning. In: IEEE fifth international conference on bio-inspired computing: theories and applications (BIC-TA), pp 555–559

Ma H, Wang Y (2009) An artificial fish swarm algorithm based on chaos search. In: IEEE fifth international conference on natural computation, pp 118–121

Neshat M, Yazdani D, Gholami E, Masoumi A, Sargolzae M (2011) A new hybrid algorithm based on artificial fishes swarm optimization and K-means for cluster analysis. IJCSI Int J Comput Sci Issues 8(4), July

Rocha Ana Maria AC, Martins Tiago FMC, Fernandes Edite MGP (2010) An augmented lagrangian fish swarm based method for global optimization. J Comput Appl Math, pp 2–20

Rocha Ana Maria AC, Fernandes Edite MGP (2011) On hyperbolic penalty in the mutated artificial fish swarm algorithm in engineering problems. In: Online conference on soft computing in industrial application, December 5–16

Shen W, Guo X, Wu C, Wu D (2011) Forecasting stock indices using radial basis function neural networks optimized by artificial fish swarm algorithm. Knowl Based Syst 24:378–385

Song X, Wang C, Wang J, Zhang B (2010) A hierarchical routing protocol based on AFSO algorithm for WSN. In: IEEE international conference on computer design and applications (ICCDA 2010), pp 635–639

Tao L, Ai-ling Q, Yuan-bin H, Xin-tan C (2009) Feature optimization based on artificial fish-swarm algorithm in intrusion detections. In: International conference on networks security, wireless communications and trusted computing, pp 542–545

Tian W, Liu J (2009) An improved artificial fish swarm algorithm for multi robot task scheduling. In: IEEE fifth international conference on natural computation, pp 127–130

Tian W, Tian Y (2009) An improved artificial fish swarm algorithm for resource leveling. In: International conference on management and service science

Tian W, Geng Y, Liu J, Ai L (2009) Optimal parameter algorithm for image segmentation. In: IEEE second international conference on future information technology and management engineering, pp 179–182

Tian W, Tian Y, Ai L, Liu J (2009) A new optimization algorithm for fuzzy set design. In: IEEE international conference on intelligent human-machine systems and cybernetics, pp 431–435

Wang L, Ma L (2011) A hybrid artificial fish swarm algorithm for bin-packing problem. In: IEEE international conference on electronic & mechanical engineering and information technology, pp 27–29

Wang C-R, Zhou C-L, Ma Jian-Wei (2005) An improved artificial fish swarm algorithm and its application in feed-forward neural networks. In: Proceedings of the fourth international conference on machine learning and cybernetics, Guangzhou, 18–21 August

Wu Y, Kiviluoto S, ZengerKai, Gao XZ, Huang X (2011) Hybrid swarm algorithms for parameter identification of an actuator model in an electrical machine. Hindawi Publishing Corporation Advances in Acoustics and Vibration, vol 2011, Article ID 637138, 12 pp. doi:10.1155/2011/637138

Xiao L (2010) A clustering algorithm based on artificial fish school. In: 2nd International conference on computer engineering and technology (ICCET), pp 766–769

XiaoLi C, Ying Z, JunTao S, JiQing S (2010) Method of image segmentation based on fuzzy C-means clustering algorithm and artificial fish swarm algorithm. In: International conference on intelligent computing and integrated systems (ICISS), pp 254–257

Xiu-xi W, Hai-wen Z, Yong-quan Z (2010) Hybrid artificial fish school algorithm for solving ill-conditioned linear systems of equations. In: IEEE international conference on intelligent computing and intelligent systems (ICIS), pp 390–394

Xu L, Liu S (2010) Case retrieval strategies of tabubased artificial fish swarm algorithm. In: IEEE second international conference on computational intelligence and natural computing (CINC), pp 365–369

Xue Y, Du H, Jian W (2004) Optimum steelmaking charge plan using artificial fish swarm optimization algorithm. In: IEEE international conference on systems, man and cybernetics, pp 4360–4364

Yazdani D, Golyari S, Meybodi MR (2010) A new hybrid algorithm for optimization based on artificial fish swarm algorithm and cellular learning automata. In: IEEE 5th international symposium on telecommunications (IST), pp 932–937

Yazdani D, Nabizadeh H, Kosari EM, Toosi AN (2011) Color quantization using modified artificial fish swarm algorithm. Int Conf Artif Intell LNAI 7106:382–391

Yuan Y, Hong Z, Ming Z, Hongqin Z, Xuyan W, He W, Jincao C, Junfang Z (2010) Reactive power optimization of distribution network based on improved artificial fish swarm algorithm. In: 2010 China international conference on electricity distribution

Yu H, Wei J, Li J (2010) Transformer fault diagnosis based on improved artificial fish swarm optimization algorithm and BP network. In: IEEE 2nd international conference on industrial mechatronics and automation, pp 99–104

Zhang M, Shao C, Li F, Gan Y, Sun J (2006) Evolving neural network classifiers and feature subset using artificial fish swarm. In: Proceedings of the 2006 IEEE international conference on mechatronics and automation, Luoyang, China, June 25–28, 1598–1602

Zhang X, Hu F, Tang J, Zou C, Zhao L (2010) A kind of composite shuffled frog leaping algorithm. In: IEEE sixth international conference on natural computation (ICNC), pp 2232–2235

Zheng T, Li J (2010) Multi-robot task allocation and scheduling based on fish swarm algorithm. In: 8th World congress on intelligent control and automation, July 6–9, Jinan, China

Zhu K, Jiang M (2010) Quantum artificial fish swarm algorithm. In: IEEE 8th world congress on intelligent control and automation, July 6–9, Jinan, China

Zhu K, Jiang M, Cheng Y (2010) Niche artificial fish swarm algorithm based on quantum theory. In: IEEE 10th international conference on signal processing (ICSP), pp 1425–1428