FAFSA: Fast Artificial Fish Swarm Algorithm

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Abstract

Most optimization problems in real life applications are often highly nonlinear. Only global optimization algorithms should be used to obtain optimal solutions. This paper introduces a new nature-inspired metaheuristic optimization algorithm, called Fast Artificial Fish Swarm Algorithm (FAFSA) for optimization and job scheduling. The basic idea of AFSA is to tradition of the behaviors of fish such as preying, swarming, and following with local fish of individual optimization of global reach.

Keywords: AFSA; Levy; Fast artificial fish swarm algorithm

1. Introduction

Most optimization problems in real life applications are often highly nonlinear. Local optimization algorithms do not give the desired performance. So, only global optimization algorithms should be used to obtain optimal solutions ([1] [2]).

It is Glover who first mentioned the term metaheuristic, when he proposed the tabu search [3]. Metaheuristics refer to a class of global heuristic optimizers. Many nature-inspired metaheuristic optimization algorithms are proposed to imitate the best behaviors in nature. Farmer et al. contribute the artificial immune system (AIS) [4]. Goldberg contributes genetic algorithms [5]. Dorigo contributes the ant colony optimization (ACO) in his PhD thesis [25]. Kennedy and Eberhart propose particle swarm optimization (PSO) [26]. Karaboga contributes Artificial Bee Colony Algorithm (ABC). Yang and Deb propose cuckoo search.

When a metaheuristic explores a search space, it has two components of intensification and diversification [27]. These two strategies originate back to the tabu search, where intensification focuses on examining neighbors of elite solutions and diversification encourages examining unvisited regions [28]. Intensification is a deterministic component and diversification is a stochastic component [29]. Metaheuristic algorithms should be designed so that intensification and diversification play balanced roles[30]. Algorithm shown in Fig. 1 is a rough algorithmic skeleton on how a metaheuristic algorithm works.

```
Create one or several start solutions,
randomly
    while termination criterion not satisfied
do
        if intensify then
            Create new solution by
        intensification;
         else
            Create new solution by
          diversification;
         end
         Update best found solution (if
necessary);
    end
return Best found solution;
```

Figure 1. Abstract algorithmic framework for metaheuristics

This abstract algorithm unifies our conceptualization of metaheuristics. But it does not show when to actually perform intensification or diversification. Additionally it does not show how to terminate the search.

We develop a new metaheuristic search algorithm called Fast Artificial Fish Swarm Algorithm (FAFSA). In this paper, we will study FAFSA and validate it against some test functions. Investigations show that it is very promising and could be seen as an optimization of the powerful algorithm of AFSA.

2. Previous Work

Method of image segmentation based on Fuzzy C-Means Clustering Algorithm and Artificial Fish Swarm AlgorithmBy 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, Artificial Fish Swarm Algorithm 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 effectiveness and feasibility.[6] WNN optimization design based on Artificial Fish-Swarm Algorithmthe problem such as parameters initialization and network structure determination is collectively referred to as the WNN optimization design. Aiming at the effect on the performance of WNN, an optimization design algorithm, which is based on Artificial Fish-Swarm Algorithm(AFSA), is proposed. The AFSA can synchronously determine the initial values of parameters and hidden layer nodes number in search space. The simulation results show it is an effective algorithm, which not only has higher accuracy and faster convergence rate but also can avoid the blindness of the WNN optimization design. [7].

Hybrid algorithm based on artificial fish swarm algorithm and tabu search in distribution network reconfigurationa distribution network reconfiguration algorithm based on artificial fish swam algorithm (AFSA) and tabu search (TS). The proposed algorithm combines the wide-area search capability of AFSA and the local optimization capability of TS, effectively overcomes the lack of using a single optimization algorithm, and improves the global optimization ability by using homeomorphism graph theory to compress the global search space. The new algorithm is applied in two testing cases with different node numbers and is compared with other algorithms; meanwhile, the parameters of algorithm are discussed in depth. The results show that the proposed algorithm is advantaged in convergence efficiency, global search ability and stability[8].

An Artificial Fish Swarm Algorithm Based on Chaos Search Artificial fish swarm algorithm is a new random optimization algorithm based on simulation of fish swarm behavior. Preliminary study shows that it has many features such as good global convergence and high convergence speed. However, it may be trapped in local optimum in the later evolution period and it has the low search accuracy. An artificial fish swarm algorithm based on chaos search is proposed, which can not only overcome the disadvantage of easily getting into the local optimum in the later evolution period, but also keep the rapidity of the previous period. Finally, the basic artificial fish swarm algorithm is compared with this method using four benchmark test functions. The experiment results demonstrate that the new algorithm proposed is better than the basic artificial fish swarm algorithm in the aspects of convergence and stability[9].

3. Artificial Fish Swarm Algorithm

The basic idea of AFSA [11] [12] is simulated fish behaviors such as swarming, preying, following with local search of fish individual for reaching the global optimum; it is random and parallel search algorithm.

3.1 Some definitions and concept

The Artificial Fish [13] [14] (AFunderstands the external perception of vision. X is the current state of an AF, Visual is the visual distance, and Xv 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 $Xnext$ 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.

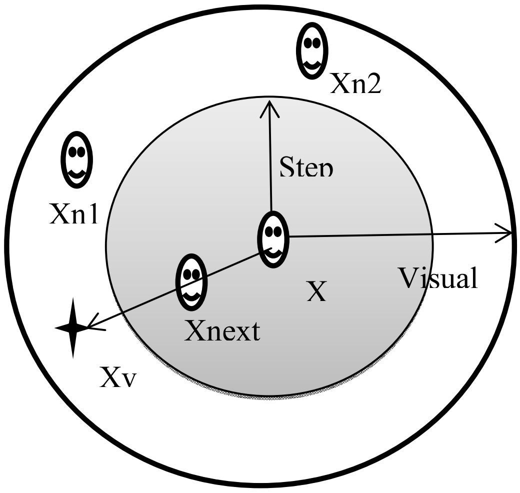


Figure 2. Vision concepts of Artificial Fish

Let X=($x_1, x_2, \dots\dots, x_n$) and Xv=($x_{1v}, x_{2v}, \dots\dots, x_{nv}$), then process can be expressed as follows:

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

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

Where Rand () produces random numbers between 0 and 1, Step is the step length, and xi 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 steplength, Visual represents the visual distance, try_number is the try number and δs the crowdfactor (0 <δ< 1). The functions include the behaviors of the AF: AF_Prey, AF_Swarm, AF_Follow, AF_Move.

3.2 The basic behaviors 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 AFSA. The basic behaviors of AF [10] are defined as follows 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 Xi 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 Yi <Yj in the maximum problem, it goes forward a step in this direction; 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.

$$X_i^{(t+1)} = X_i^{(t)} + Visual.Rand() \quad (4)$$

(2) AF_Swarm: The fish will assemble in groups naturally in the moving process, which is a kind of living habits in order 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 nf be the number of its companions in the current neighborhood (dij<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;

$$X_i^{(t+1)} = X_i^{(t)} + \frac{X_c - X_i^t}{||X_c - X_i^t||} Step\ Rand() \quad (5)$$

Otherwise, executes the preying behavior. The crowd factor limits the scale of swarms, and more AF only cluster at the optimal 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 (dij<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 surroundings is not very crowded, it goes forward a step to the companion Xj ,

$$X_i^{(t+1)} = X_i^{(t)} + \frac{X_j - X_i^t}{||X_j - X_i^t||} Step\ Rand() \quad (6)$$

Otherwise, executes the preying behavior.

(4) AF_Move: Fish swim in random way 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.

$$X_i^{(t+1)} = X_i^{(t)} + Visual.Rand() \quad (7)$$

4. The Fast Artificial Fish-Swarm Algorithm (FAFSA)

In the AFSA, there are many parameters that have impacts on the final optimization result, in this paper; we only consider the parameter $Rand()$ we will use Brownian motion and Levy flight Algorithms

4.1 Definition of brownian motion

Brownian motion [15] [16] is closely linked to the normal distribution. Recall that a random [17] variable $X$is normally distributed with mean μ and variance σ^2 if

$$\mathbb{P}\{X > x\}\frac{1}{\sqrt{2\pi\sigma^2}}\int_x^\infty e^{-\frac{(u-\mu)^2}{2\sigma^2}}\,du \quad for\ all\ x \in \mathbb{R} \tag{8}$$

Definition a real-valued stochastic process $\{B(t) : t \geq 0\}$ is called a (linear) Brownian motion with start in $x \in \mathbb{R}$if the following holds:

- $B(0)$,
- The process has independent increments, i.e. for all times $0 \leq t_1 \leq t_2 \leq \ldots$: the increments $B(t_n) - B(t_n - 1), B(t_n - 1) - B(t_n - 2), \ldots, B(t_2) - B$ are independent random variables,
- For all t and h , the increments $B(t + h) -$ are normally distributed with expectation zero and variance h,
- Almost surely, the function t $t \mapsto$ is continuous.

We say that $\{B(t) : t > 0\}$ is a standard Brownian motion if $x = 0$.

For the moment let us step back and look at some technical points. We have defined Brownian motion as a *stochastic process* $\{B(t) : t > 0\}$ which is just a family of (uncountably many) random variables $\omega \longmapsto B(t, \omega)$ defined on a single probability space$(\Omega, \mathcal{A}, \mathbb{P})$. At the same time, a stochastic process can also be interpreted as a *randomfunction* with the sample functions defined by $\omega \longmapsto B(t, \omega)$. The *sample path properties* of a stochastic process are the properties of these random functions, and it is these properties we will be most interested in in this book.

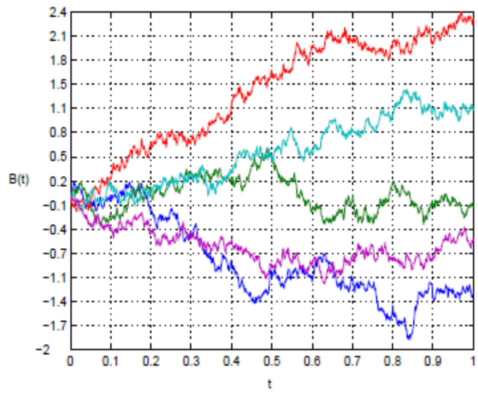


Figure 3. Brownian motion

By the finite-dimensional distributions of a stochastic process $\{B(t) : t > 0\}$ we mean the laws of all the finite dimensional random vectors

$$\big(B(t_1), B(t_2), \ldots, B(t_n)\big), for\ all\ 0 \leq t_1 \leq t_2 \leq \ldots \leq t_n.$$

To describe these joint laws it suffices to describe the joint law of $B(0)$ and the increments

$$(B(t_1) - B(0), B(t_2) - B(t_1), \ldots, B(t_n) - B(t_n - 1)), \mathit{for\ all}\ 0 \leq t_1 \leq t_2 \leq \ldots \leq t_n.$$

This is what we have done in the first three items of the definition, which specify the finite-dimensional distributions of Brownian motion. However, the last item, almost sure continuity, is also crucial, and this is information which goes beyond the finite-dimensional distributions of the process in the sense above, technically because the set $\{\omega \in \Omega : t \mapsto B(t,\omega) \text{ continuous}\}$is in general not in the algebra generated by the random vectors $(B(t_1), B(t_2), \ldots, B(t_n)), n \in \mathbb{N}$.

4.2 Definition of levy flight

A Levy flight [18] is the random walk [19] a move lengths probability distribution that heavy tail. When know as walk away in an area larger than the distance of one, the steps that are in random directions isotropic

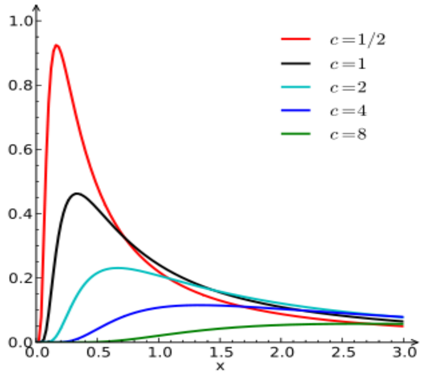


Figure 4. Levy Flight

Definition: The probability density function of the Levy distribution over the domain $X \geq \mu$ is

$$f(x; \mu, c) = \sqrt{\frac{c}{2\pi}} \frac{e^{-\frac{c}{2(x-\mu)}}}{(x-\mu)^{3/2}} \tag{9}$$

Where μ is the location parameter and c is the scale parameter. The cumulative distribution function is

$$F(x; \mu, c) = \operatorname{erfc}\left(\sqrt{\frac{c}{2(x-\mu)}}\right) \tag{10}$$

Where $\operatorname{erfc}(z)$ is the complementary error function? The shift parameter μ has the effect of shifting the curve to the right by an amount μ, and changing the support to the interval $[\mu, \infty)$. Like all stable distributions, the Levy distribution has a standard form $f(x; 0,1)$ which has the following property:

$$f(x; \mu, c)dx = f(y; 0,1)dy$$

Where y is defined as

$$y = \frac{x-\mu}{c} \tag{11}$$

5. Evaluation

Let us review some test functions to test the performance of optimization algorithms. Then we compare the proposed algorithm with a common previous work.

5.1 Standard Test functions

There are many benchmark test functions to test the performance of optimization algorithms, though there is no unified standard list ([20], [21]). There are certain guidelines for selecting the test function. The most important criteria are to contain nonlinear non-separable problems and to include high-dimensional functions with a large number of local optima ([22]).
Our test framework contains the following four functions

De Jong function [23]:

$$f_1(x) = \sum_{i=1}^{n} \tag{12}$$

Rosenbrock function [24]:

$$f_2(x) = \sum_{i=1}^{n-1}(100(x_i^2 - x_{i+1}) + (1 - x_i \tag{13}$$

The generalized Ackley function:

$$f_3(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n} \cos 2\pi x_i\right) + 20 + \tag{14}$$

The generalized Rastrigin function:

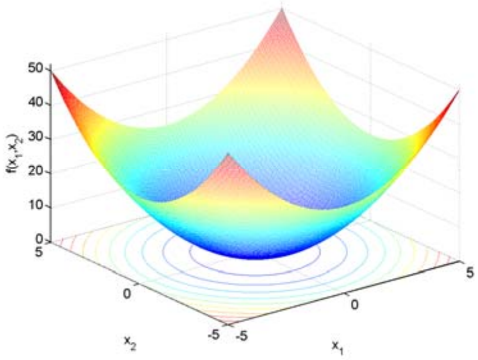
$$f_4(x) = 10n + \sum_{i=1}^{n}(x_i^2 - 10\cos(2\pi x \tag{15}$$

5.2 Results

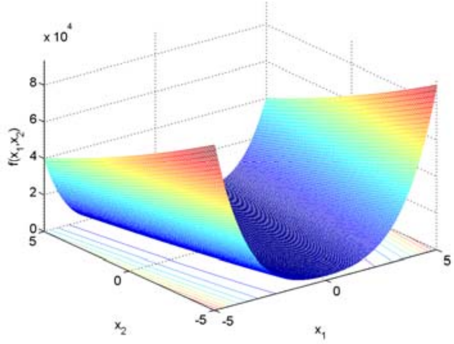
We conduct 100 simulation runs of the algorithm and Matlab implementation of AFSA. For the four test functions described above: De Jong (32 dimension), Rosenrbrock(16 dimension), Ackley (128 dimension), (6) Rastrigin (default dimensions). Table 1 shows standard deviation and its percentage success rate of finding the global optima,

Table 1. Comparison of AFSA with FAFSA

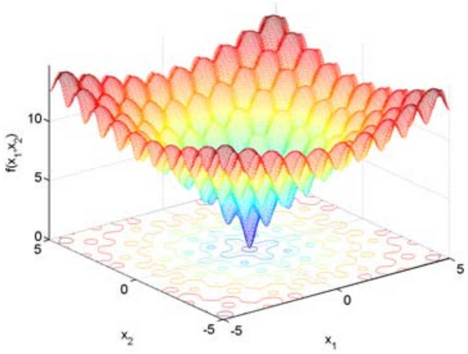
Functions	AFSA	FAFSA
De Jong	590	539
Ackley	1107	803
Rosenrbrock	2338	1987
Rastrigin	4470	4030



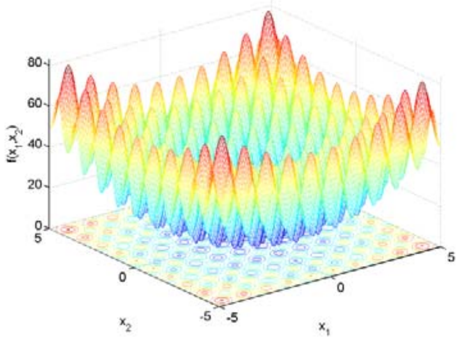
a) De Jong function



b) Rosenbrock function



c) Ackley function



d) Rastrigin function

Figure 5. Standard Test functions

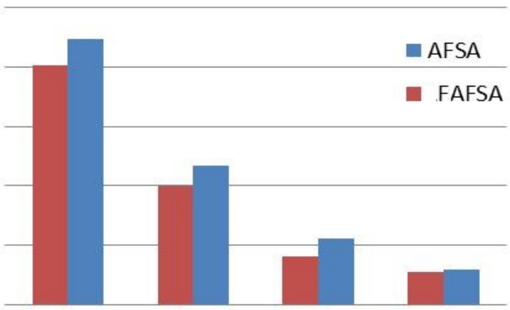


Figure 6. Comparison of AFSA and FAFSA

6. Conclusion and Future Work

We develop a new metaheuristic search algorithm called Fast Artificial Fish Swarm Algorithm (FAFSA). In this paper, we study FAFSA and validate it against some test functions. Investigations show that it is very promising and could be seen as an optimization of the powerful algorithm of AFSA.

We consider applying the proposed algorithm in Job Scheduling in Grid Computers. It is known that the job scheduling is NP-complete, and thus the use of heuristics is the de facto approach to deal with this practice in its difficulty. The proposed is an imagination to fish swarm, job dispatcher and Visualization gridsim to execute some jobs. [10]

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