RESEARCH ON FUZZY C- CLUSTERING RECURSIVE GENETIC ALGORITHM BASED ON CLOUD COMPUTING BAYES FUNCTION

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ABSTRACT

Aiming at the problems of poor local search ability and precocious convergence of fuzzy C-cluster recursive genetic algorithm (FOLD++), a new fuzzy C-cluster recursive genetic algorithm based on Bayesian function adaptation search (TS) was proposed by incorporating the idea of Bayesian function adaptation search into fuzzy C-cluster recursive genetic algorithm. The new algorithm combines the advantages of FOLD++ and TS. In the early stage of optimization, fuzzy C-cluster recursive genetic algorithm is used to get a good initial value, and the individual extreme value pbest is put into Bayesian function adaptation table. In the late stage of optimization, when the searching ability of fuzzy C-cluster recursive genetic is weakened, the short term memory function of Bayesian function adaptation table in Bayesian function adaptation search algorithm is utilized. Make it jump out of the local optimal solution, and allow bad solutions to be accepted during the search. The improved algorithm is applied to function optimization, and the simulation results show that the calculation accuracy and stability of the algorithm are improved, and the effectiveness of the improved algorithm is verified.

KEYWORDS

fuzzy C-clustering recursive genetic algorithm; Bayesian function adaptation search; Function optimization

1. INTRODUCTION

In recent years, many optimization algorithms have been proposed to solve optimization problems, and heuristic methods have attracted more and more attention. Among heuristic algorithms, compared with other intelligent algorithms,FOLD++ has the advantages of being easy to describe, easy to implement, fewer parameters to be adjusted, no gradient information of objective function is needed, and only function values are relied on. FOLD++ has been proved to be an effective method to so The larger the crack depth is, the larger the signal amplitude is. So the crack depth can be determined quantitatively according to the amplitude of the detected signal. As can be seen from FIG. 11, when the frequency is 1.3~2.0MHz, the amplitude of crack signal amplitude is small, but the rule between frequency and amplitude can also be analyzed. When detecting the crack with a depth of 0.2mm, the amplitude of the signal amplitude caused by the change of frequency is small, which proves that the signal can penetrate the depth of 0.2mm when the frequency is 1.3~2.0MHz. When detecting the depth crack of 0.8mm, the amplitude of the signal amplitude caused by the change of frequency is more obvious, which is switched from 1.6MHz orithm [3], Li Rongjun and Chang Xianying proposed to introduce the idea of clustering behavior in the fish swarm algorithm into fuzzy C-cluster recursive genetic algorithm [4]. These improved algorithms have solved the problem that the fuzzy C-cluster recursive genetic algorithm

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falls into the local optimum in the late search period to some extent, but there are still some defects in the premature convergence and convergence speed.

In this paper, a new TS-fold ++ algorithm is proposed based on the Bayesian function adaptation table in Bayesian function adaptation search. The basic idea is to use fuzzy C-clustering recursive genetic algorithm to search in the early stage of the algorithm, and make full use of its fast and global convergence. When FOLD++ algorithm searches slowly in the late stage, it uses the short term memory function of the Bayesian function adaptation table of Bayes function to make it jump out of the local optimal solution and turn to other fields of solution space.

2. Fuzzy C-Clustering Recursive Genetic Algorithm (TS-Fold++)

2.1. Basic Principles of Fold++ Algorithm

FOLD++[1] algorithm is a new intelligent optimization algorithm proposed by J. Kenney and R. Eberhart in 1995. The basic idea is derived from the study and simulation of bird foraging behavior. This model can be used to solve the optimal problem. When FOLD++ algorithm is used to solve the optimization problem, the solution of each problem is regarded as a fuzzy C-cluster recursive inheritance without mass and volume in the optimization space. The location of each fuzzy C-cluster recursive inheritance is regarded as a solution in the solution space, and the flight speed is dynamically adjusted according to the comprehensive analysis results of individual and group flight experience. Suppose that in the D-dimensional space, after k iterations, the speed and position of the I-th fuzzy C-cluster recursive inheritance are respectively denoting as:, each fuzzy C-cluster recursive inheritance preserves its own best position, and the individual extremum and global extremum are denoting as pbest and gbest respectively. Therefore, the speed and position update of fuzzy C-clustering recursive inheritance i during k iterations can be expressed by the following formula:

$$\mathrm{f}_{\beta}\left(x\right)=\left(1-\frac{1}{\beta}\right)^{+}\delta\left(x\right)+\frac{\sqrt{\left(x-a\right)^{+}\left(b-x\right)^{+}}}{2\pi\beta x} \quad (1)$$

$$\psi_{m,n}\left(t\right)=\left|a\right|^{-m/2}\psi\left(a_0^{-m}t-nb_0\right),m,n\in Z \quad (2)$$

Where: w is the inertia weight; c1 and c2 are learning factors, which adjust the maximum stride length of individual best fuzzy C-clustering recursive inheritance and global best fuzzy C-clustering recursive inheritance direction flight, usually 2.0; r1 and r2 are random numbers on [0,1].

2.2. Basic Principle of Bayes Function

Bayesian function adaptation search, a deterministic iterative optimization algorithm, was first proposed by Glover in At the priority point, there is a problem of large error in reconstruction of damaged data of graph surface wheel. Therefore, a damaged data reconstruction method based on N-S square wave transform with undetermined mbda parameters of non-downsampled contour is proposed in this paper. The velocity components u,v,w and pressure p in that direction. At the output of the neural network, Auto-differentiation is added to the sampling wheel. The N-S square with undetermined mbda parameters can be perceived to obtain the structure part and texture part of the damaged data of the compressed image. The distribution function of the damaged data can be obtained by using Bayesian compressed sensing. With Autmbda parameter undetermined N-S square O-value and variance, the maximum priority point of the reconstruction dynamic differential of the boundary of the damaged data region is obtained by using the non-down-sampling wheel differential (auto-profile transform to determine the broken perception), and the non-down-sampling direction filter is designed to give the image damaged data rgence rate, but the search performance depends on the given initial solution. A good initial solution can make the Bayes function converge to the global optimal solution quickly, but a poor initial solution may greatly reduce the convergence rate of the algorithm. Therefore, in application, other algorithms are usually used to give a better initial solution.

3. Put Forward The Improvement Method

3.1. Adaptive Adjustment of Inertia Weight

In the fuzzy C-cluster recursive genetic algorithm, inertia weight is a very important parameter. When w is large, it is beneficial to improve the global search ability of the algorithm, but the local search ability is poor. When w is small, the local search ability of the algorithm can be enhanced, but the search ability of the new domain is poor. The linear decline strategy (LDW) proposed by Shi and Eberhart is widely used at present: w is initialized at 0.9 and linearly decreases to 0.4 as the number of iterations increases. As shown in the equation:

$$\tilde{f}_{\beta}(x)=(1-\beta)\delta(x)+\beta f_{\beta}(x) \qquad (3)$$

Where, kmax is the maximum number of iterations, and k is the current number of iterations. Because FOLD++ algorithm is a nonlinear motion process in the optimization process of solution space, in addition, the maximum number of iterations is difficult to predict, so linear decline strategy has certain defects.

In this paper, Shi and Eberhart later proposed a strategy of adaptive adjustment of w based on individual fitness values of fuzzy C-clustering recursive genetics [5], and the inertia weight coefficient changes automatically with the change of fuzzy C-clustering recursive genetic goals. The calculated expression is as follows:

$$\frac{1}{N}\mathbf{H}^{H}\mathbf{y}=\frac{1}{N}\mathbf{H}^{H}\mathbf{H}\mathbf{x}+\frac{1}{N}\mathbf{H}^{H}\mathbf{n}\xrightarrow{N\to\infty}\mathbf{x}+\frac{1}{N}\mathbf{H}^{H}\mathbf{n}$$

In fact, wmax and wmin respectively represent the maximum and minimum values of w, fi is the current objective function value of fuzzy C-clustering recursive inheritance, favg and fmin are the average and minimum target values of all fuzzy C-clustering recursive inheritance, respectively.

3.2. Introduction of Search Strategies

The basic idea of the traditional Bayesian function adaptation fuzzy C-cluster recursive genetic algorithm (T-fold ++) algorithm [6] is based on the framework of the fuzzy C-cluster recursive genetic algorithm. Firstly, the preliminary search is carried out to obtain a good initial value, and at the same time, the Bayesian function adaptation table is established to record the current optimal location gbest. In the next iteration process, Determine whether the adaptive value of each fuzzy C-clustering recursion genetic update position is better than the forbidden object, if so, update the taboo object; If not, the updated location is judged to be prohibited. If the location is prohibited, the initialization speed is updated again to update the fuzzy C-clustering transmission genetic speed and location. If not, no processing is done, and the speed and position of fuzzy C-clustering recurrence genetic update are preserved.

Method improvement: In the traditional TS-fold ++ algorithm, the previous gbest of the whole population is recorded in the Bayesian function adaptation table. With the increase of the scale of Bayes function, it is far from enough to rely on the gbest recorded in A non-destructive testing method based on induction principle, suitable for the detection of conductor materials, it is very sensitive to fatigue cracks and subsurface corrosion defects, high sensitivity, good accessibility. For eddy current detection, the blade quality information is contained in the voltage (current) signal received by the measuring coil in the eddy current sensor. Among the output signals received by the measuring coil, what can characterize the discontinuity such as blade crack defects is the variation of voltage (current) signal, or the eddy current sensor is respectively placed in the blade end and the place containing cracks and other discontinuity defects cursive inheritance, and pbest1, pbest2... pbestL is arranged in descending order according to the optimal value of the objective function. In addition, to ensure global search, pbest1, pbest2... pbestL is isolated from dis at a certain distance.

FOLD++ in the search process of solution space, if the speed of fuzzy C-clustering recursive inheritance updates slowly, fuzzy C-clustering recursive inheritance loses its search ability, because the states of the first, second and third parts in formula (1) approach 0, and the position x, pbest and gbest of fuzzy C-clustering recursive inheritance are almost the same. And so you slowly fall into local optimality. At this time, from the established taboos table, in addition to pbest1, select pbest2, pbest3... One of pbestL is used for the velocity renewal equation. The fuzzy C-cluster recursive inheritance may escape from the local solution space because the fuzzy C-cluster recursive inheritance searches the pbest that has been nearby. When a newer pbest is searched or there is no update in a while, pbest1 is used in the velocity update equation and the original FOLD++ is used again to update the equation. In addition, since the Bayesian function adaptation table established by each iteration is independent, it is impossible to make all fuzzy C-cluster inheritance in the Bayesian function adaptation state. And because each fuzzy C-cluster recursive inheritance uses the history value in the pbest table and gbest information of its own search process, it can ensure good search performance.

In order to improve the algorithm and enhance the global search capability of solution space, the following two points are emphasized in TS:

(1) Upper limit of inheritance rate renewal of fuzzy C-clustering transmission:

$$\mathbf{A}^{-1} = \sum_{n=0}^{\infty} \left(\mathbf{X}^{-1} \left(\mathbf{X} - \mathbf{A} \right) \right)^{n} \mathbf{X}^{-1} \qquad (5)$$

Average grain distance of Bayes function:

$$\min_{\hat{\mathbf{x}}} \Phi(\hat{\mathbf{x}}) = \frac{1}{2}(\hat{\mathbf{x}}, \mathbf{A}\hat{\mathbf{x}}) - (\mathbf{b}, \hat{\mathbf{x}}) \qquad (6)$$

The distance between individuals in the table:

$$\hat{\mathbf{x}} = \left\{ \min_{\hat{\mathbf{x}}} \Phi(\hat{\mathbf{x}}) = \frac{1}{2}(\hat{\mathbf{x}}, \mathbf{A}\hat{\mathbf{x}}) - (\mathbf{b}, \hat{\mathbf{x}}) \right\} \square \left\{ \mathbf{A}\hat{\mathbf{x}} = \mathbf{b} \right\} \qquad (7)$$

Where, D is the dimension of the search space, xspan is the range of variables, and Len is the diagonal maximum length of the search space.

Since there is no actual mechanism to control the genetic speed of fuzzy C-clustering recursive genetic algorithm, it is necessary to limit the maximum speed. When the speed exceeds this threshold, the speed is set to Vmax. When the Bayesian function adaptation state is on or off, the average grain distance D(t) of the Bayes function in each iteration is calculated. When $D(t)<Dmin$, the Bayesian function adaptation state is on. When pbest is updated or when the taboo period is out of date, the taboo state closes. Each iteration of Bayesian function adaptation state on or off is independent of each other;

(2) When establishing the update pbest table, the update of the pbest table takes into account the distance between each pbest. When the position x evaluation function of fuzzy C-cluster recursive inheritance is better than the evaluation function in the table, it is updated. The condition used for the new pbest is one of the following two conditions.

(a) when the distance is greater than dis;
(b) When the distance is less than dis, the function value of x is better than that of pbest in the table.

When none of the above conditions are met, it is not updated.

In summary, the flow of the improved TS-fold ++ algorithm can be described as follows:

(1) Initialization algorithm parameters: scale N, dimension, inertia weight, learning factor, maximum number of iterations nitermax, minimum limit threshold of mean grain distance of Bayesian function, Bayesian function adaptation length L, etc., initialization fuzzy C-clustering recursive genetic Bayesian function genetic speed and position;
(2) The initial Bayes function is randomly generated to calculate the adaptive value of each fuzzy C-cluster recursive inheritance, where the solution corresponding to the minimum value is the current optimal solution of the population gbest; The current position of each fuzzy C-cluster transmission inheritance is pbest; Set the iteration number niter=1;
(3) Determine whether the current iteration times reach the maximum iteration times nitermax; if not, update niter=niter+1; If yes, the current optimal solution of the population is output gbest;
(4) The dynamic inertia weight was calculated according to formula (4), and the flight velocity and position of fuzzy C-cluster transmission inheritance were calculated according to formula (1) and (2). In the iterative process, if $vi>vmax$, $vi=vmax$; if $vi<-vmax$, $vi=-vmax$;
(5) Determine the Bayesian function adaptation state of the switch, if on, as described in 3.2 update rules, from pbest2, pbest3... In pbestL, roulette method is used to select pbest for formula (2) updating speed of fuzzy C-clustering transmission inheritance; If close, select pbest1 from the pbest table, and update the speed and location of fuzzy C-clustering transmission inheritance from equations (1) and (2);
(6) Update the pbest table;
(7) Update gbest;
(8) Judge whether the termination condition is met. If the termination condition is met, output the result and end the algorithm; otherwise, go to step (3).

4. SIMULATION COMPARISON

In order to verify the performance of TS-Fold ++ algorithm, three classical reference functions, Sphere function,Rastrigrin function and Bayes function, are used for testing and analysis.

(1) Sphere function:

$$\alpha^{(k)} = \frac{\left(\mathbf{r}^{(k)}, \mathbf{r}^{(k)}\right)}{\left(\mathbf{r}^{(k)}, \mathbf{A}\mathbf{p}^{(k)}\right)} \quad (-100 \le x_i \le 100)$$

This function is a nonlinear symmetric unimodal function, which is separable between different dimensions and relatively simple. It is mainly used to test the optimization accuracy of the algorithm. The global minimum point is xi=0(i=1,2... ,n), the global minimum is f(xi)=0.

(2) Rastrigrin function:

$$\frac{|1-\omega| + (\omega-\gamma) l_i + \omega u_i}{1-\gamma l_i} \ge \frac{u_i}{1-l_i}$$
$$(-5.12 \le x_i \le 5.12)$$

Based on Sphere function, this function uses cosine function to generate a large number of local minima, which is a typical complex multimodal function with a large number of local optima. It is easy to make the algorithm fall into local optima, but cannot get the global optimal solution. The global minimum point is xi=0(i=1,2... ,n), the global minimum is f(xi)=0.

(3) Bayes function:

$$\begin{cases} \hat{\mathbf{x}}^{(k+1)} = \mathbf{L}_{\gamma,\omega}\hat{\mathbf{x}}^{(k)} + \omega(\mathbf{I}-\gamma\mathbf{L})^{-1}\mathbf{D}^{-1}\mathbf{b}, \ k = 0,1,2\cdots \\ \mathbf{L}_{\gamma,\omega} = (\mathbf{I}-\gamma\mathbf{L})^{-1}\left[(1-\omega)\mathbf{I} + (\omega-\gamma)\mathbf{L} + \omega\mathbf{U}\right] \end{cases}$$
$$(-50 \le x_i \le 50)$$

This function is a multi-modal function of rotating, non-separable and variable dimension. With the increase of dimension, the range of local optima becomes narrower and narrower, which makes it relatively easy to find the global optimal value. The global minimum point is xi=0(i=1,2,... n), and there are numerous local minima, and the global minimum is f(xi)=0.

In the calculation of the above three functions, the search space dimension D was set as 10,20 and 50, the number of initializing population was set as 30, the taboo length L was set as 5, Dmin=0.001, and the maximum number of iterations was set as 1000. Random tests are carried out on each function, and the two algorithms mentioned in literature [1] and [6] are compared. The simulation results are shown in Table 1.

Table 1 Comparison of optimization test results of the three algorithms

Optimal function	Vector	Mean			Optimal		
		FOLD ++	(LDW) TS-FOLD++	Refined TS-FOLD++	Standard FOLD++	(LDW) TS-FOLD++	Refined TS-FOLD++
SphereFold+	10	5.45	0.10	0.70	1.35	1.02	0.00
	30	0.23	0.34	3.79	0.16	0.01	0.11
	60	1.62	2.09	6.95	1.16	6.95	1.16
Rastrigin	10	7.59	0.42	1.35	1.02	1.75	1.89
	30	27.32	12.12	0.16	0.01	8.68	7.59
	60	6.95	1.16	40.34	45.57	6.95	1.16
Bayes	10	1.75	1.89	0.60	3.50	1.35	1.02

	30	8.68	7.59	0.42	0.20	0.16	0.01
	60	6.95	1.16	0.13	1.09	0.98	0.01

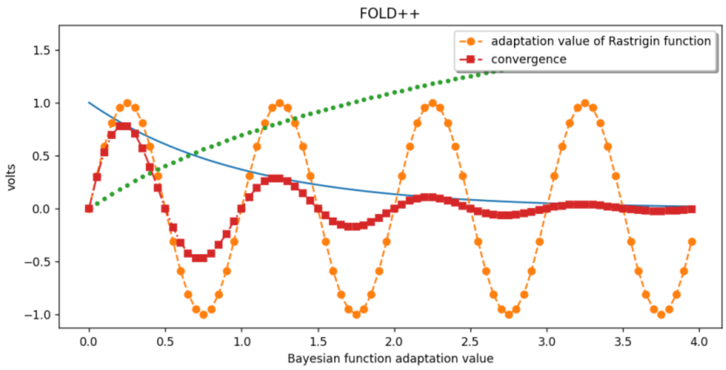

Figure 1 Changes in the adaptation value of Rastrigin function

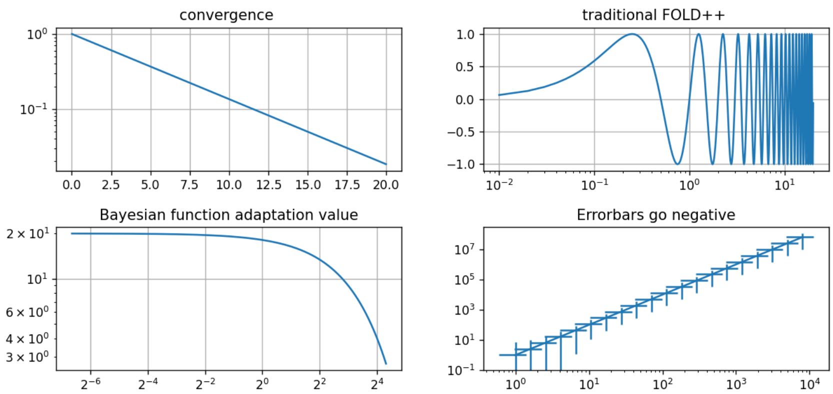

Figure 2 Changes of Bayesian function adaptation value

As can be seen from the results analysis in Table 1, the improved TS-Fold ++ effect is significantly superior to that of FOLD++ and (LDW) TS-Fold ++ when dealing with multi-peak functions Rastrigin and Bayes. Combined with the characteristics of Bayes function, the results show that the improved TS-fold ++ algorithm makes it relatively easy to find the global optimal value, and with the increase of dimension, the precision is higher.

Figure 1 and Figure 2 respectively list the changes of the adaptation values of Rastrigin function and Bayes function in the optimization process. As can be seen from the figure, the improved TS-Fold ++ method can better find the optimal solution in a limited number of iterations than the linear inertia TS-Fold ++ and the traditional FOLD++ method. The convergence times are greatly reduced and the convergence accuracy is also improved.

5. Conclusion

In this paper, the taboo idea of Bayes function is integrated into FOLD++ algorithm. The advantages of the two algorithms are complementary, which not only overcomes the shortcomings of FOLD++ algorithm with weak local se Parameters or unknown structures. At this time, it is necessary to use part of the sampled data to assist the solution, and add a term to the loss function to make the network output consistent with the sampled data value at the given sampling point. If the partial differential equation has a few unknown parameters, the solution method is similar to the forward problem. If some terms of the system are unknown, it is necessary to construct the set of candidate terms when solving the reverse problem, and then use sparse re The neural network optimizer optimizes the constraint of the process and the above loss function. The constraints and optimizers of the constant path include Adam, L-BF, GS, etc. The decline curve of the loss function in the optimization process is as follows. When the constraint and the loss function of the loss path decrease to the sufficient sum of the constraint of the foot path, it can be considered that the solution of the neural network approximately satisfies the constraint of the partial differential equation and the constraint of the boundary condition. When the problem program is constrained and solvable, the output of the neural network is the partial differential equation to be solved he other two algorithms.

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