Optimal Design of FIR Filter Based on Improved Artificial Bee Colony Algorithm

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***Abstract*— The optimal design of FIR filter is very important, and using artificial bee colony algorithm can optimize fir parameters, but it also has the disadvantages of slow convergence speed and easy to fall into local optimum. Therefore, an improved artificial bee colony algorithm is proposed in the paper, which introduced the random disturbance term of chi-square distribution and convergence operator. The improved algorithm is applied to the parameter optimization design of low-pass and band-pass FIR filters, and the design effect is remarkable, especially the filter has small ripple in the passband and stopband, flat amplitude, and good attenuation characteristics.**

Keywords-component: FIR filter design; Artificial bee colony algorithm; Parameter optimization

I. Introduction

Digital filter plays an important role in Image Processing and Pattern Recognition, and FIR has been widely used in actual applications because of its advantages in linear phase and stability. Some commonly used traditional methods such as window function[1], frequency sampling[2],etc. can only obtain the filter coefficients of limited accuracy. The window function method designs to use a suitable window function to intercept the ideal unit impulse response $h_d(n)$ in the time domain, so that the designed filter can approximate the ideal characteristics. And the frequency sampling method is to optimize the filter design by setting transition points in the frequency domain. These years, plenty of researches has been done on FIR digital filter optimization, Vicente A[3] et al. proposed three different finite impulse response (FIR) smoothing algorithms, using the maximum likelihood FIR estimation, which is robust against uncertain noise statistics and model parameters, and also independent of the initial states of each finite horizon. And in reference[4], the weighted Frobenius norm is employed as a cost function to design a local unbiased FIR filter. The problem of designing the filter coefficients can be transformed into the solution of the optimal value of a multidimensional continuous function, and the ABC algorithm is available to optimize it.

Artificial Bee Colony is a bionic intelligent optimization algorithm firstly proposed by Turkish scholar Karaboga[5] in 2005,which simulates the intelligent search behavior of the honey bee colony. With the advantages of few control parameters, easy implementation, strong robustness, etc., more and more researchers have paid attention to it. The current research on ABC algorithm mainly focuses on three aspects: designing new search strategies, mixing with other algorithms, applications in practical life and engineering. In order to further improve the design accuracy of FIR filter, this paper will propose a new improved ABC algorithm, which mainly introduces the random interference term of chi-square distribution and convergence operator to obtain a satisfactory optimization effect of FIR filter.

II. The Improved Artificial Bee Colony Algorithm

A. The description of the basic artificial bee colony algorithm

The ABC algorithm is derived from the simulation of the intelligent honey collection mechanism of honeybee colonies. Bees have self-organization and division of labor and cooperation during honey collection. According to this group cooperation mechanism, they constantly find high-quality nectar sources and share information with their peers through waggle dance to find the best nectar source. Correspondingly, in the ABC algorithm, the nectar source location represents the fitness solution of the optimization problem, and the honey quantity represents the quality of the solution. Each individual needs to remember the location and fitness value of the respective nectar source and retain the optimal solution during the exploration process. Three basic elements: food source, employed foragers and unemployed foragers consist the minimal search model for bee colonies to generate swarm intelligence.And artificial bee colonies contain three types of individuals: employed bees, scout and onlookers. Half of the colony consisted of employed bees and half of onlookers, there is only one employed bee for each nectar source, and the employed bees and the onlookers are responsible for carrying out the extraction process. When a high-quality nectar source is found, the honeybees will further exploit the nectar source, and the equation for exploiting the nectar source is:

$$V_{ij} = X_{ij} + \Phi_{ij}(X_{ij} - X_{kj}) \tag{1}$$

Here V_{ij} is the new nectar location, X_{ij} is the original nectar location, and Φ_{ij} is a random number between [-1,1].

When a nectar source is found to have a very low profitability after being searched for a limited number of times, the onlookers will turn into scouts and execute the exploration process of a new nectar source. It is precisely because of the negative feedback mechanism of bees on the exploration and exploitation of food sources that the algorithm is conducive to jumping out of the shackles of local optimum when optimizing multi-peak functions and avoiding premature convergence. The equation for searching for a new nectar source is:

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$$X_i^{\,j} = X_{\min}^{\,j} + rand\,(0,1)(X_{\max}^{\,j} - X_{\min}^{\,j}) \tag{2}$$

Here i is the number of the nectar source, j is the dimension of the population, X_{min} and X_{max} are the respectively lower and upper limits of the nectar source location taking values. The equation for the probability of food source selection is:

$$f(i) = \frac{fit(i)}{\sum_{i=1}^{SN} fit(i)} \tag{3}$$

Here $f(i)$ refers to the probability that the i th food source is selected, $fit(i)$ is the fitness of the i th food source, and SN is the total number of food sources. The equation for calculating fitness is:

$$fit(i) = \begin{cases} \dfrac{1}{1+f_i}, f_i > 0 \\ 1 + abs(f_i), f_i < 0 \end{cases} \tag{4}$$

B. The improvement of the ABC

The positive feedback mechanism existing in the ABC algorithm will reduce the population diversity, and the bee colony is very prone to converge at the local optimum point, that will cause the search stagnant. This kind of phenomenon is most obvious in the optimization of solving the multi-peak function. The key to this problem lies in the exploitation of the nectar source. Since the update of nectar source information is in one direction, and the limitation of this update limits the optimization of the algorithm, which leads to premature convergence of the colony to a local optimum. The chi-square distribution is a probability distribution in statistics, and its distribution properties depend on the value of degrees of freedom. Suppose there are n mutually independent random variables *A1,A2...An*, they all obeying the standard normal distribution, then the sum of squares of these n random variables obeying the standard normal distribution is called chi-square. When the degrees of freedom are large, the chi-square distribution approximates to the normal distribution, and its probability density equation is:

$$f_k(x) = \frac{(1/2)^{k/2}}{\Gamma(k/2)} x^{k/2-1} e^{-x/2} \tag{5}$$

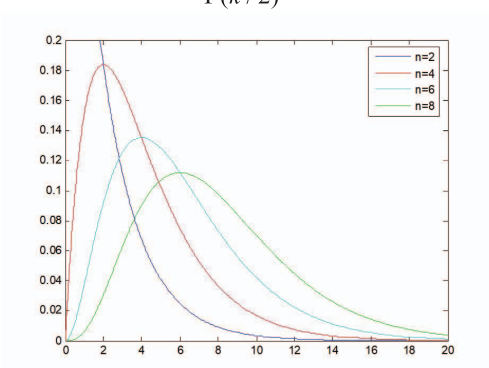

Figure 1 Probability density curve of chi-square distribution

Figure 1 shows the probability density curve of the chi-square distribution in the interval [0, 20] with different degrees of freedom. As the degree of freedom increases, the curve is closer to the normal distribution. The key to the ABC algorithm is population initialization. The chi-square distribution is introduced into the equation for honey bee extraction of food sources, and because the chi-square distribution can produce asymptotically distributed random numbers with strong random perturbation ability, it can provide conditions for the generation of new individuals, effectively avoiding the occurrence of stagnation and improving the convergence speed of the algorithm. The improved equation is:

$$V_{ij} = X_{ij} \bullet \text{chi-square} + \Phi_{ij}(X_{ij} - X_{kj}) \tag{6}$$

At the same time, in order to avoid the algorithm falling into local optimum, a convergence operator d is introduced. Let:

$$d = \frac{1}{n}\sum_{i=1}^{n}(f_i - f_{av})^2 \tag{7}$$

Here f_i is the fitness of the i th bee, f_{av} is the fitness of the current bee colony, $f_{av} = \frac{1}{n}\sum_{i=1}^{n} f_i$, and d is the embodiment of the difference between the fitness of each nectar source and the average fitness, reflecting the convergence degree of the bee colony.

When $d= 0$, it means that the nectar source exploitation can no longer be updated and the local optimum or global optimum is reached. If at this time, the value of the optimal objective function determines that it tends to be locally optimal, the nectar source location will be updated according to Equation (2).In this way, it can effectively disperse the swarms after clustering, help the swarms to get rid of the local optimal, expand the search range, and improve the search ability.

The steps of improving ABC algorithm are as follows:

Step1: Initialize the algorithm, randomly generate SN nectar sources, calculate the quality of nectar sources, find the optimal value, and set the maximum number of iterations *max_cycle*.

Step2: Set the number of iterations *cycle*=1;

Step3: The picking bee performs a domain search according to Equation (6) to generate a new solution, calculates its fitness value, and greedily selects *Vij* and *Xij*;

Step4: Calculate the probability of each nectar source being selected, and select the food source by the roulette selection method;

Step5: Calculate the convergence degree of the bee colony according to Equation (7), if it reaches the local optimum, then randomly generate a new nectar source to replace the old nectar source according to Equation (2);

Step6: Record the optimal nectar source and fitness value currently searched by the ABC algorithm;

Step7: *cycle*=*cycle*+1, if *cycle*<*max_cycle* is satisfied, return to step 3, otherwise the algorithm ends.

C. Benchmark function simulation comparison

To illustrate the efficiency of the improved ABC algorithm by comparing the functions for optimization, three typical test functions were selected experimentally using Matlab, with 1000 iterations of each function and a number of 50 nectar sources.

$f1$: Ackley:

$$f_1(x) = -20e^{\left(-0.02\sqrt{\sum_{i=1}^{n}\frac{x_i^2}{n}}\right)} - e^{\left(\sum_{i=1}^{n}\frac{\cos(2\pi x)}{n}\right)} + 20 + e, x_i \in [-100,100]$$

$f2$: Rastrigin:

$$f_2(x)=\sum_{i=1}^{n}(x_i^2-10\cos(2\pi x_i)+10), x_i\in[-200,200]$$

*f*3: Sphere:

$$f_3(x)=\sum_{i=1}^{n}x_i^2, x_i\in[-100,100]$$

The optimization curves of the algorithm for the three test functions are shown in Figures 2-4.

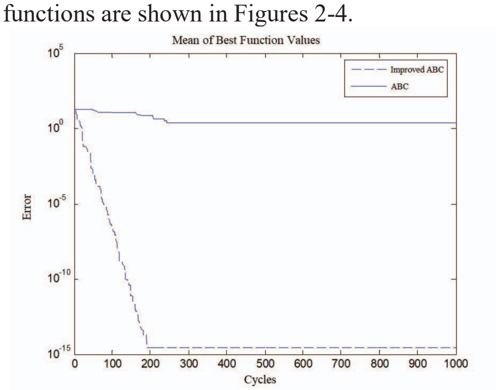

Figure 2 Ackley function curve

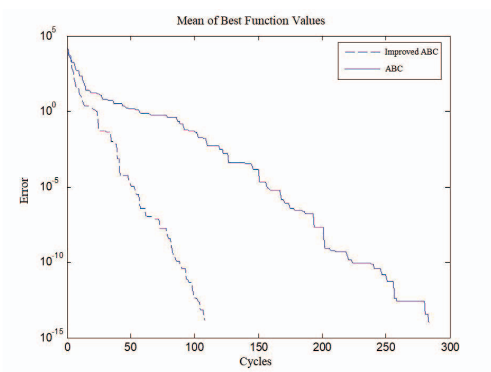

Figure 3 Rastrigin function curve

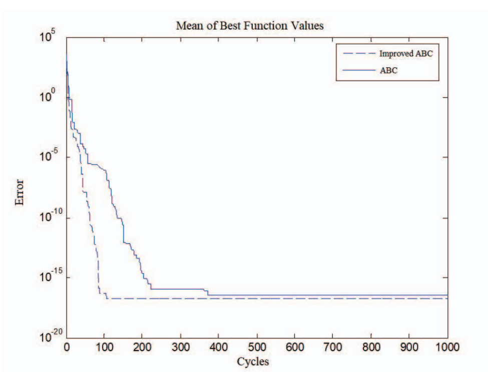

Figure 4 Sphere function curve

Ackley and Rastrigin are two multi-peaked functions with multiple local extremes in the definition domain, and it is difficult to find the global optimum for the general function. Sphere function is a unimodal function with a global minimum at *f*(0). From the simulation results, the performance of the improved ABC algorithm is significantly better than the original bee colony algorithm, which overcomes the shortcomings of slow convergence of single-mode functions and easy to fall into local optimum for multi-mode functions in the process of optimization.

III. The FIR Filter Optimized by Improved ABC Algorithm

A. The basic theory of FIR filter

The unit impulse response of the *N*-order FIR filter is *h*(0), *h*(1)...*h*(*N*-1), and the relationship between its input and output is:

$$y(n)=\sum_{k=0}^{N-1}h(k)x(n-k) \tag{8}$$

Here *x*(*n*) is the input to the system and *y*(*n*) is the output. The output of the filter is only related to the current and past inputs. the FIR filter satisfies the linear phase condition,(i.e. $h(n)=\pm h(N-1-n)$),its frequency response can be expressed as:

$$H(e^{jw})=\sum_{n=0}^{N-1}h(n)e^{-jwn} \tag{9}$$

If the ideal frequency response is $H_d(e^{jw})$, the approximate filter characteristics and ideal filter characteristics are required to satisfy the minimum mean square error criterion[13]:

$$E(e^{jw})=\sum_{i=1}^{M}(|\sum_{n=0}^{N-1}h(n)e^{-jwn}|-|H_d(e^{jw})|)^2 \tag{10}$$

The optimal design of the FIR filter can be mapped to a problem of solving the minimum using ABC algorithm. And based on the minimum mean square error function, we can obtain a suitable set of filter pulse coefficients.

B. Optimization results and analysis of filter parameters

As analyzed above, to reduce the errors due to the interception of infinitely long impulse responses or the dispersion of sampling points, the improved ABC algorithm is used to optimize the parameters of the filter. According to the minimum mean square error criterion, the error caused by the sampling point value can be reduced, and better filter performance can be obtained by the improved ABC algorithm.

In the simulation experiments, Matlab is used to simulate and optimize the design of the low-pass FIR filter of order 33 with the maximum number of iterations set to 1000 using the frequency sampling method and the improved ABC algorithm, respectively.

In the simulation experiments, we optimized the design of the low-pass FIR filter of the order 33 respectively using the frequency sampling method and the improved ABC algorithm.The simulation software is Matlab, the maximum number of iterations set to 1000 and the ideal characteristics of the low-pass filter are:

$$H_d(e^{jw})=\begin{cases}1,0\le w<0.3\pi\\0,0.3\pi\le w\le\pi\end{cases} \tag{11}$$

The amplitude response curves of the low-pass filter designed by the frequency sampling method and the modified ABC algorithm are shown in Figure 5-6.

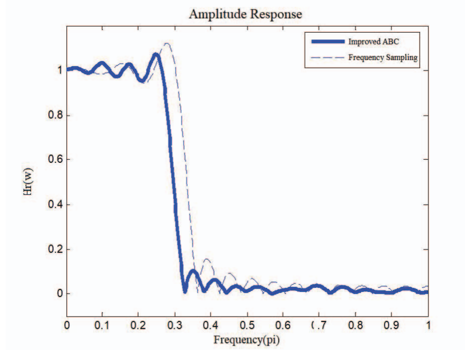

Figure 5 Amplitude-frequency characteristic curve of lowpass filter

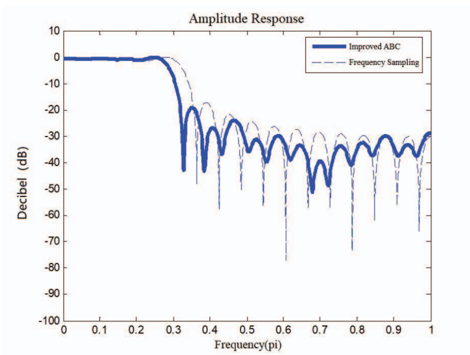

Figure 6 Logarithmic amplitude-frequency characteristic curve of lowpass filter

As we can see from the simulation curves in the above two figures, the filter designed with the improved ABC algorithm have smaller ripples in the passband and stopband, a narrower transition band and a flatter amplitude, and the stopband attenuation obtained is better than that of the frequency sampling method. In addition, it is found that the error caused by the improved ABC algorithm is also very small. Obviously, when using the minimum mean square error function as the fitness function, the filter designed by the improved ABC algorithm has the minimum error and better amplitude characteristics.

Design the FIR bandpass filter in the same way, with the same initial conditions as above, and the ideal filter characteristics are:

$$H_d(e^{jw}) = \begin{cases} 1, 0.4\pi \le w < 0.7\pi \\ 0, others \end{cases} \tag{12}$$

The obtained bandpass filter amplitude response curves are shown in Figure 7-8.

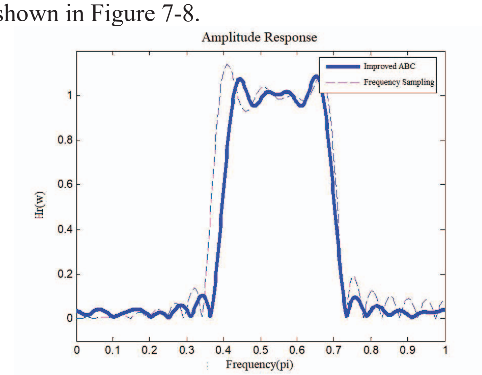

Figure 7 Amplitude-frequency characteristics curve of bandpass filter

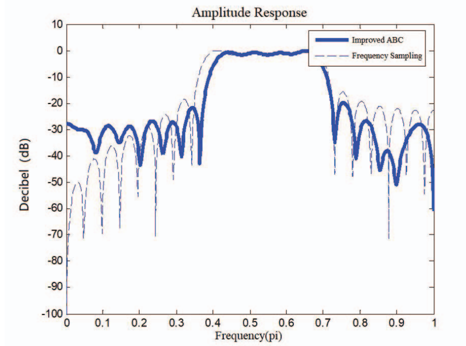

Figure 8 Logarithmic amplitude-frequency characteristic curve of bandpass filter

The design results show that this design method is also adapted to bandpass filters. In conclusion, the improved ABC algorithm can be used to obtain satisfactory filter characteristics and is an effective design method.

IV. CONCLUSIONS

By analyzing the shortcomings and deficiencies of the traditional ABC algorithm, this paper proposes an improved ABC algorithm, which introduces the random interference term of chi-square distribution and convergence operator, which effectively avoids the algorithm from falling into local optimum, expands the search range, and is efficient and feasible.

The improved ABC algorithm is applied to FIR filter design, and the fitness function of the filter is modeled according to the minimum mean square error criterion, which can obtain satisfactory filter performance, especially with small passband and stopband ripple, flat amplitude and good attenuation characteristics..

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