An Improved Quantum Particle Swarm Optimization and Its Application in System Identification

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Abstract: In order to improve convergence speed and precision of optimization in quantum particle swarm optimization (QPSO), an improved quantum particle swarm optimization (IQPSO) algorithm was presented. Chaotic sequences were used to initialize the origin angle position of particle, mutation operation algorithm was used to increase diversity of population and avoid premature convergence. The proposed algorithm was applied to identify the classic adaptive infinite impulse response (IIR) model, the results show the validity of IQPSO.

Key Words: Quantum particle swarm optimization, System identification, Adaptive IIR filter

1 INTRODUCTION

Quantum particle swarm optimization is an optimization method based on the principles of quantum computing [1]. The algorithm extends the ability of traversing solution space by using a kind of coding scheme by probability amplitude. The particles moving ways based on quantum rotation gate make the search more sophisticated and performance of algorithm is improved to some extent. But as same as PSO, the optimized performance of QPSO depends on the initial choice of parameters and it is easy to fall into local optimum.

In order to improve the convergence speed and optimization precision of QPSO, this paper presents an improved QPSO algorithm which is based on chaotic initialization and mutation operation. Firstly, the likelihood of global convergence increases through initializing the position of each particle with chaotic sequence because chaotic sequence has uniformity, repeatability and not ergodic[2]; secondly, the mutation operator in IQPSO algorithm aims to increase the population diversity and avoid premature convergence, which can reduce the number of invalid iterations and improve the convergence rate. Simulation results show that the proposed algorithm can do well in adaptive IIR filter identification.

2 Quantum particle swarm optimization

2.1 Standard PSO algorithm

Suppose the position of the i-th particle in D-dimensional solution space is expressed as: $x_i=(x_{i1},x_{i2},\dots,x_{id})$, the speed is $v_i=(v_{i1},v_{i2},\dots,v_{id})$, the individual extreme $p_i=(p_{i1},p_{i2},\dots,p_{id})$, global minimum of the population $p_g=(p_{g1},p_{g2},\dots,p_{gd})$. Particle updates its velocity and position with the following formula:

$$\begin{cases} v_{id}(t+1)=w\times v_{id}(t)+c_1\times r_1\times[p_{id}(t)-x_{id}(t)]+\ c_2\times r_2\times[p_{gd}(t)-x_{id}(t)] \\ x_{id}(t+1)=x_{id}+v_{id}(t+1) \end{cases} \quad (1)$$

Where c_1 and c_2 are constants named acceleration coefficients corresponding to cognitive and social behavior. r_1,r_2 are two independent random numbers uniformly distributed in the range of $[0,1]$. w is the inertia weight which is determined by the following formula:

$$w=w_{\max}-\frac{w_{\max}-w_{\min}}{n_{iter\max}}\times n_{iter} \quad (2)$$

Where: $n_{itermax}$ is the total number of iterations; n_{iter} is the current iteration; w_{max} is the ceiling of inertia weight; w_{min} is the threshold of inertia weight; inertia weight w controls the effect of previous speed of the particles on the current speed of the particles, the larger w can enhance global search capability of PSO and the smaller one can enhance the local search capability. Generally, the value of each component in v_i can be clamped to the range $[V_{imin}, V_{imax}]$ to control excessive roaming of particles outside the search space$[X_{imin}, X_{imax}]$.

2.2 Quantum particle swarm optimization

In QPSO, the probability amplitude of the quantum bits is used as the particle encoding of the current position directly. Particles movement is implemented through quantum rotation gate. The update algorithm of the qubit argument incremental [3-5] as follows:

$$\Delta\theta_{id}(t+1)=w\times\Delta\theta_{id}(t)+c_1\times r_1\times(\Delta\theta_l)+c_2\times r_2\times(\Delta\theta_g) \quad (3)$$

Here: w,c_1,c_2,r_1,r_2 have the same meaning as standard PSO and the values are also similar; $\Delta\theta_l$ equals the local best angles minus current angles; $\Delta\theta_g$ equals the global best angles minus current angles; the calculation formulas of them are as follows[6]:

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$$\Delta\theta_l = \begin{cases} 2\pi + \theta_{ilj} - \theta_{ij}, & \theta_{ilj} - \theta_{ij} < -\pi \\ \theta_{ilj} - \theta_{ij}, & -\pi \le \theta_{ilj} - \theta_{ij} \le \pi \\ -2\pi + \theta_{ilj} - \theta_{ij}, & \theta_{ilj} - \theta_{ij} > \pi \end{cases} \quad (4)$$

$$\Delta\theta_l = \begin{cases} 2\pi + \theta_{gj} - \theta_{ij}, & \theta_{gj} - \theta_{ij} < -\pi \\ \theta_{gj} - \theta_{ij}, & -\pi \le \theta_{gj} - \theta_{ij} \le \pi \\ -2\pi + \theta_{gj} - \theta_{ij}, & \theta_{gj} - \theta_{ij} > \pi \end{cases} \quad (5)$$

QPSO can extend the solution space by using a kind of coding scheme which is based on probability amplitude, and the particles moving ways by quantum rotation gate can make the search become more sophisticated. Therefore, the algorithm performance can be improved in some extent.

3 Improved quantum particle swarm optimization

3.1 The improvement of initial population

Due to the initial angle of population in quantum particle swarm optimization algorithm is given by randomly distributed strategy, the ergodic ability of initial population is limited. Chaos is a class of nonlinear phenomena with fine inherent structure. The main characteristics of chaotic are pseudo-randomness, ergodicity and sensitivity to initial conditions. Since ergodic can be act as an effective mechanism to avoid it sliding into local minima in search process, chaos theory has become a novel and potential optimization tool. Using the characteristics of chaotic sequence to initialize the population of particle can be used to find a better solution and accelerate the algorithm convergence. A widely used system evidencing chaotic behavior is the logistic map, which can be expressed as follows[8]:

$$L(i+1) = \mu L(i)[1 - L(i)] \quad (6)$$

Where: μ is a constant, which is used to control the degree of chaos ($\mu \in [3.56, 4.0]$); $L(i) \in (0, 1)$, $i=1, 2, \ldots, D$.

3.2 Mutation operation

As precocious phenomenon exists in QPSO, we will use mutation operator to avoid precocious phenomenon. The mutation operation is achieved by the quantum-NOT gate, and the equation is as follows:

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \cos(\theta_{id}) \\ \sin(\theta_{id}) \end{bmatrix} = \begin{bmatrix} \cos(\theta_{id} + \pi/2) \\ \sin(\theta_{id} + \pi/2) \end{bmatrix} \quad (7)$$

Quantum-NOT gate is used to realize mutation operation if $r < p_m$, the best position and steering angle of the particle are still the same when $p_m \leqslant r$. Here, r is a random number between (0, 1), p_m is mutation probability.

3.3 Description of improved QPSO algorithm

The steps of improved QPSO algorithm proposed in this paper can be described as follows:

Step1：Set the parameters of QPSO, such as population size, the number of variables and the inertia factor and so on.

Step2：Use the formula (6) to generate the initial population.

Step3：Use the fitness function to evaluate the initial position of each particle, calculate the fitness value of each particle positions. If the current position of the particle position was better than the best memory position, then replace it with the current location; if the current global optimum position was better than the global optimum position which is searched so far, then replace it with global optimum position.

Step4: Use the formula (3) to update the position of the particle.

Step5: Equation (7) is used to carry mutation operation

Step6: Return Step3 to cyclic calculation until satisfy the convergence conditions or maximum limits. Convergence condition is determined by the specific problem.

4 Identification of adaptive IIR filters

Adaptive IIR filter is a recursive filter with infinite impulse response. In recent years, there has been a number of more mature algorithms about adaptive IIR filter. However, as the error surface of the adaptive IIR filtering algorithm is very complex, the effects of them were not well.

In this paper, two groups of classical adaptive IIR filter are selected to identify by using the improved quantum particle swarm optimization. Parameters of IQPSO are as follows: population size is 25; inertia factor w=0.5; $c1$=$c2$=0.2; mutation probability p_m=0.05; maximum number of iterations is 300; μ=3.9.

Tab. 1 Identification result of classic self-adapting IIR filter

The results contrast	Example 1	Example 2
The transfer function	$(0.173z^{-1}+0.102z^{-2})/(1-1.425z^{-1}+0.496z^{-2})$	$(z^{-1}-0.9z^{-2}+0.81z^{-3}-0.729z^{-4})/(1-0.04z^{-1}-0.277\ 5z^{-2}+0.210\ 1z^{-3}-0.14z^{-4})$
Identification results	$(0.096z^{-1}+0.257z^{-2})/(1-1.297z^{-1}+0.378\ 5z^{-2})$	$(0.998\ 6z^{-1}-0.963\ 5z^{-2}+0.977z^{-3}-0.832\ 1z^{-4})/(1-0.086z^{-1}-1.972z^{-2}+0.238\ 3z^{-3}-0.199\ 9z^{-4})$

The fitness function of the algorithm is:

$$J = 50 \times \sum_{i=1}^{t_{LP}} e_i^2 \quad (8)$$

Where: e_i is the difference between the identification result and the actual results; t_{LP} is regulation time of the adaptive filter. The identification results are shown in Figure 1 and Figure 2. From the figures, we can know that no matter what kind of adaptive IIR filter, our algorithm has better effects than paper [8] in identification error.

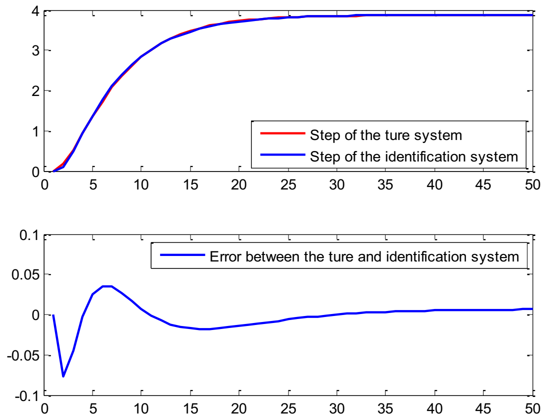

Fig. 1 Identification result of case1

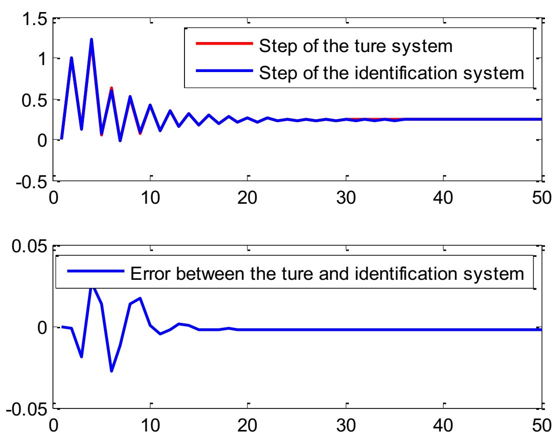

Fig. 2 Identification result of case2

5 Conclusion

In this paper, chaotic sequences were used to initialize the origin angle position of particle, mutation operation algorithm was used to increase diversity of population and avoid premature convergence. Simulation results show that the proposed algorithm can do well in adaptive IIR filter identification.

REFERENCES

[1] Shen Jia-ning,Sun Jun,Xu Wenbo. System identification based on QPSO algorithm[J]. Computer Engineering and Applications,2009,45（9）：67-70.

[2] Wang Zijie, Huang Yu, Han Pu et al. Active Disturbance Rejection Control of Steam Temperature System for Cycle Fluidized Bed Boiler[J]. Journal of Chinese Society of Power Engineering, 2010, 30(1):31-35

[3] Zhang Zhisheng. Quantum-behaved particle swarm optimization algorithm for economic load dispatch of power system[J]. Expert Systems with Applications 2010:1800–1803.

[4] Jiao Songming,Han Pu,Huang Yu,et al. Fuzzy quantum genetic algorithm and its application research in thermal process identification [J].Proceedings of the CSEE,2007,27(5)：87-92.

[5] Zhu Haimei , Wu Yongping. A PSO algorithm with high speed convergence[J]. Control and Decision, 2010,25(1):20-24.

[6] Li Shiyong, Li Panchi. Quantum particle swarms algorithm for continuous space optimization[J].. Chinese Journal of Quantum Electronics. 2007, 24(5):569-574.

[7] Bipul Luitel, Ganesh Kumar Venayagamoorthy. Quantum inspired PSO for the optimization of simultaneous recurrent neural networks as MIMO learning systems[J]. Neural Networks , 23 (2010) 583_586.

[8] Liu B, Wang L, J in Y H, et al. Improved particle swarm optimization combined with chaos[J]. Chaos Solitons & Fractals, 2005 , 25 : 1261-1271.

[9] LIU Fu-cai, GAO Xue, WU Shi-chang Model reference adaptive IIR recursive filters identification algorithm[J]. Computer Engineering and Design, 2008, 29(12):3170-3172.