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A Modified Particle Swarm Optimization Algorithm

Jie He*[1], Hui Guo[2]
[1] Department of Computer Science, Wuzhou University
Wuzhou, 543002, China, +86-774-5825722
[2] Department of Electronics Information Engineering, Wuzhou University
Wuzhou, 543002, China, +86-774-5828708
*Corresponding author, e-mail: hejie1213@126.com[1], gxguohui@163.com[2]

Abstract

In optimizing the particle swarm optimization (PSO) that inevitable existence problem of prematurity and the local convergence, this paper base on this aspects is put forward a kind of modified particle swarm optimization algorithm, take the gradient descent method (BP algorithm) as a particle swarm operator embedded in particle swarm algorithm, and at the same time use to attenuation wall (Damping) approach to make fly off the search area of the particles of size remain unchanged and avoid the local optimal solution, with three input XOR problem to testing the improvement of the particle swarm optimization algorithm and the results showed that the improved algorithm not only increase global optimization ability, but also avoid the prematurity, convergence problem.

Keywords: *Particle swarm optimization; Premature; BP Neural Networks*

1. Introduction

Traditional BP learning algorithm is slow convergence speed, easy to fall into local minimum value, in order to solve this problem.,the current many researchers use simulated annealing, genetic algorithm and other global search method in the training of the neural network training. Compared with simulated annealing method (SA), genetic algorithm (GA) is a kind of parallel random search method based on natural selection and genetic evolutionary mechanism, Its learning speed is usually better than simulated annealing method, but its complex genetic operation makes the neural network takes time as the problem size and complexity to exponential growth, lack of effective mechanism in local search, and convergence near the optimal solution slow and even stall.. Particle swarm optimization (PSO) is a kind of calculation method based on the theory of swarm intelligence (SI), Is a kind of model in the field of SI, It retains a global search strategy based on population. Current particle swarm algorithm has been used in neural network learning [1, 2], and achieved good results, similar to genetic algorithms, however, the conventional particle swarm optimization (pso) algorithm in solving complex optimization problems also exist in the phenomenon such as early maturity, convergence and stagnation,? although some improvements in the optimization of the performance of the algorithm is improved to a certain extent, but the algorithm itself, the nature of the problem has not be solved. In order to solve the problems that exist in particle swarm algorithm training neural network such as premature and slow convergence speed, This paper combines the particle swarm optimization (pso) algorithm and BP,and an improved particle swarm optimization algorithm is proposed. The purpose of the method is to effectively complex the global parallel searching of particle swarm algorithm and the advantages of the BP's local deterministic searching, to speed up the convergence rate, and to avoid falling into local extremum.

2. Improved Particle Swarm Optimization

2.1. Particle Swarm Optimization

Particle Swarm Optimization (Particle Swarm Optimization PSO) Put forward by Dr. Eberhart and Dr. Kennedy in 1995, It originated from bird predation behavior of the simulation, First, initialize a random population. Each particle in the population represents a possible

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solution to solve the problem. Each particle has its own position and speed, In the process of each iteration, Particles remember, follow the current iteration of the optimal particle,by tracking two "extreme" to update their position and velocity. The two extreme value is individual extreme value respectively, that is the particles themselves to find the optimal solution; The global extremum, the entire population to find the optimal solution. After Particles found the two extreme value in the iterative process, Particle according to the formula (1) (2) to update your own position and speed [3, 4].

$$v_{i,d}^{(t+1)} = \omega \cdot v_{i,d}^{(t)} + c_1 \cdot rand_{id} \cdot (pbest_{i,d}^{(t)} - x_{i,d}^{(t)}) + c_2 \cdot rand_{gd} \cdot (gbest_{d}^{(t)} - x_{i,d}^{(t)}) \quad (1)$$

$$x_{i,d}^{(t+1)} = x_{i,d}^{(t)} + v_{i,d}^{(t+1)} \quad (2)$$

Here “t” is the number of iterations, “□” is the inertia factor , $x_{i,d}^{(t)}$ is the position vector of the particles. $v_{i,d}^{(t)}$ Is the position vector of the particles. $pbest_{i,d}^{(t)}$ is the optimal particle “i” position corresponding to the d-dimensional position coordinates. $gbest_{d}^{(t)}$ is the populations to achieve the best position in the d-dimensional position coordinates corresponding. c_1、c_2 are acceleration factor.. $rand_{id}$、$rand_{gd}$ are Uniformly distributed random numbers of [0,1],Above (1) Velocity update $v_{i,d}^{(t+1)}$ has three components. First, "momentum" part, explains the current state of the particles; Second, "cognitive" part, considering the particles experience; Third, "social" part, on behalf of particles of the "social" role. Particles in the search space by their own information $pbest$ and groups information $gbest$ to move to the target point.

2.2. The Description of the Improved Particle Swarm Optimization Algorithm

The process is as followed All the particles in the algorithm in each generation groups first evolution by PSO, By the formula (1) and (2) update the speed and position of the profile of each particle, and calculate the fitness value of each particle; According to the the particles fitness value selects one or several adaptable particles, These particles are called elite individuals, The elite individuals not directly come into the next generation algorithm groups, But by the BP operator in improving on their performance. that to say, use the BP operator in elite individuals near the area to develop more excellent performance of particle location. And all the particles are guided by their next generation populations evolve rapidly. These newly developed elite particles with populations in the remaining particles constitute the next generation of hybrid algorithm populations. The method makes the population size of the particles in the algorithm execution process using attenuated wall [5] (Damping) unchanged, maintaining the diversity of particle. Improved particle swarm optimization algorithm on the whole in the next generation of the PSO algorithm groups into individuals generated by BP algorithm, Structure of the process is shown in Figure 1.

2.3. Improved Particle Swarm Optimization Algorithm Description

The assumed algorithms particles population size P, The number of elite individuals are selected for N, Used in each generation evolution the BP operator training times for the L, Algorithm evolutionary times is T, We will perform a BP operator elite number of individuals in the population size, the proportion is defined as the degree of mixing of the algorithm (N / P), Equal to 0 when the algorithm is the degree of mixing of the entire neural network weights and threshold combination completely rely on the PSO optimized hybrid algorithm will degenerate into conventional PSO algorithm to train the neural network can be seen; algorithm mixing equal to 100%, andzero initial velocity of a single particle in the population, the hybrid algorithm degenerates to traditional BP algorithm learning neural network, in which the number of training T * L. This method the number of elite individuals N should be under specific circumstances to determine the appropriate value for the reduction of the general case of the calculated amount of N does not exceed 10% of the population size P.

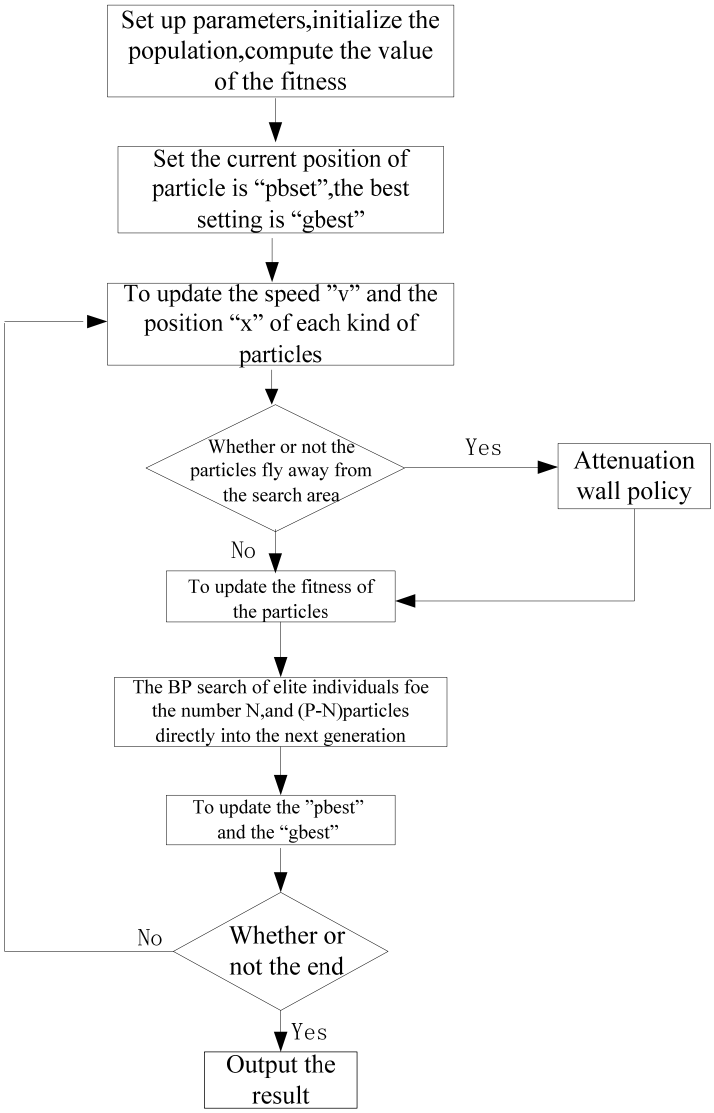

Figure 1. Algorithm structure flowchart

In PSO algorithm, Inertia factor ω according to the literature 4 decreases linearly. Usually update as (3)

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \times iter \tag{3}$$

Here $iter_{\max}$ is the biggest evolution of algebra, $iter$ is the algebra for this evolution. However, in the algorithm execution process, there is still a small portion of the particles will fly to the outside the region of the solution space, the search for the particles may pass through the boundaries, optimal solution is difficult to obtain the problem, this article uses Document 5 attenuation wall (Damping) method (such asas shown in Figure 2, and the position of the particle is placed on the boundary, the direction of the velocity is negated, the value of the velocity to reduce a random quantity, so the optimization is within the search area, so that particles of the same population size, keeping particlesdiversity.

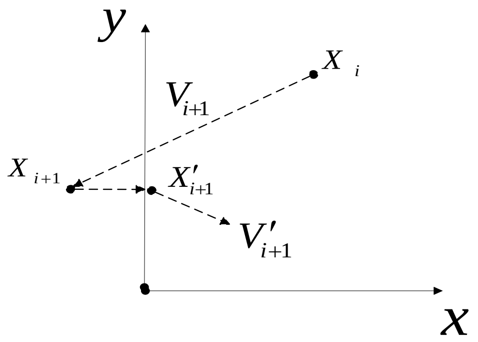

Figure 2. Attenuation wall schematic diagram

Improved particle swarm optimization algorithm BP operations driven by the amount of correction of the weights of the way, that the amount of correction of the weights between the neural network node m and node n from equation (4)

$$\Delta\omega_{nm}(t+1) = \alpha\Delta\omega_{nm}(t) + \eta\delta_n(t)y_m(t) \tag{4}$$

Here the amount of correction of the conventional BP, α is algorithm, and $y_m(t)$ is the momentum term inertia coefficient for the output node m.

The above gradient particle swarm method for three-layer neural network training, through the experiments coding network weights and threshold values constitute a vector, the vector is a particle in the particle swarm algorithm. If three feedforward network structure is taken as the n_{in} $n_{in} - H - n_{out}$ form, you need to optimize network $n_{in} \cdot H + H \cdot n_{out} + H + n_{out}$ parameters.

Firstly, in the search space randomly generated initial population P particles constitute, through the the adaptation function defined groups each particle fitness value, the definition of appropriate learning network search for an optimal combination of parameters using the methodwith the smallest function value.

2.4. Improved Particle Swarm Optimization Characteristics

The the gradient particle swarm learning algorithm combining the PSO evolution and BP search, and mixed cross training the neural network, which is based on the following factors to consider. PSO is a parallel stochastic global search method, by sharing group information and memory particles prior experience and access to knowledge to improve particle adaptability; PSO has strong global search capability, however, the lack of effective local fine-tuning ability, search when solving complex optimization problems the late high adaptability particles probability is significantly reduced, so that the convergence rate is limited. BP algorithm is a simple deterministic local search method, with a strong performance in the partial adjustment along the gradient descent direction can quickly find the local optimal solution, but BP algorithm on the choice of the initial position is very sensitive, and can not ensure that the optimal solution is globally optimal. The combination of the two methods can effectively integrated PSO and BP algorithm advantages can give a good tradeoff between PSO global exploration and BP local development; the combination give the PSO evolution and BP search provided between a mutually full role, i.e. the BP operation performed in the PSO each generation of optimization Solutions based on the optimal solution can be obtained with higher accuracy, while the optimized solution returned to the particle swarm optimization process serve as the optimum position and guide the rapid evolution of the groups to share their location information between the two algorithms complement each other and promote each other to reach a common optimization purposes. Departed the search area for the particles and in the optimization process, using attenuated wall method can guarantee that the number of particles of the population unchanged, to ensure the diversity of particle.

BP operation as an operator sub embedded PSO optimization process, thus increasing the PSO evolution generation needed to calculate the amount of CPU time; the algorithm groups limited elite particles BP, participate in small particles, the small number of iterations,Therefore, the computational complexity of the algorithm of PSO each evolutionary generation increase is not more BP count particle Swarm algorithm can significantly improve the processing efficiency of the algorithm information.

3. Experimental Examples

In this paper, the three-input XOR improved particle swarm optimization test, and comparison with other neural network learning methods. The three-input exclusive-or function has the following input-output relationship:

$$\begin{cases} (-1,-1,-1),(-1,+1,+1) \\ (+1,-1,+1),(+1,+1,-1) \to -1 \\ (-1,-1,+1),(-1,+1,-1) \\ (+1,-1,-1),(+1,+1,+1) \to +1 \end{cases} \tag{5}$$

Take (5) 8 group of samples to learn the structure of the 3-4-1 three-layer feedforward neural networks, network learning weights and threshold parameter of 21, network learning fitness function defined for formula (6)

$$E = \frac{\sum_{t=1}^{8} (y_1^d(t) - y_1(t))^2}{8} \tag{6}$$

Use GA, PSO and this paper improved particle swarm method for learning network, and compare their algorithms learning outcomes. Each algorithm parameters are set as follows:

The initial network training parameters are in the range [-10,10] uniform random population size P = 30; Method to improve particle swarm parameters $c_1 = c_2 = 2$, inertia weight factor ω with the evolution of algebra from linear 0.9 down to 0.2, the maximum speed of the particles $v_d^{\max} = 0.4 \cdot x_d^{\max}$, each evolutionary generation BP operations elite number of individuals N = 1, BP-operator learning step $\eta = 0.30$, the inertia coefficient $\alpha = 0.25$,training times L = 150; non-linear ranking selection GA algorithm, arithmetic crossover and uniform mutation genetic manipulation, the best individual probability of selection is $q = 0.1$ i, crossover probability is taken as two probability experiments $p_c = 0.9$ and $p_c = 0.6$,and mutation probability is $p_m = 0.1$; PSO algorithm parameters c_1 c_2 and ω value with improved particle swarm method; three algorithms are evolutionary 30 generations and repeated 20 times to test separately, the best, the worst, the average fitness value and standard deviation of the 20-run results compareThe results are shown in Table 1.

Table 1. Comparison of Testing Results for 3-Input XOR Problem

Learning method	The value of fitness			The standard deviation
	The best fitness	The worst fitness	The average value of fitness	
GA（p_c=0.6）	1.1126E-01	0.7127	0.4014	0.1758
GA（p_c=0.9）	2.0756E-01	0.6876	0.4526	0.1506
PSO	2.9680E-02	0.5566	0.2521	0.1653
The method of this Paper	0	2.7513E-27	1.3806E-28	6.1510E-28

As can be seen from Figure 3, GA and PSO algorithm learning network accuracy is not high, the GA and PSO is a global optimization of parallel algorithms, but weak on local fine-tune the ability; improvement can also be seen from the table in this articleparticle swarm learning methods adaptation value is much smaller than the corresponding values of GA and PSO algorithm, effectively improve the optimized performance of the algorithm by PSO and BP cross-linking; In addition, the method is 20 times repeated training fitness value of the standard deviation is also much lower thanthe corresponding values of GA and PSO algorithm, PSO with BP hybrid cross-training network optimization solutions improve reliability.

Figure 3 shows the three algorithms 20 run average fitness value evolution curve comparison, this method in comparison with the other two methods, and its adaptation curve decline seen from FIG steeper and more close to the globally optimal value minE = 0, Description of the proposed method to train the network convergence rate is much faster than GA and PSO algorithm and optimization solution accuracy.

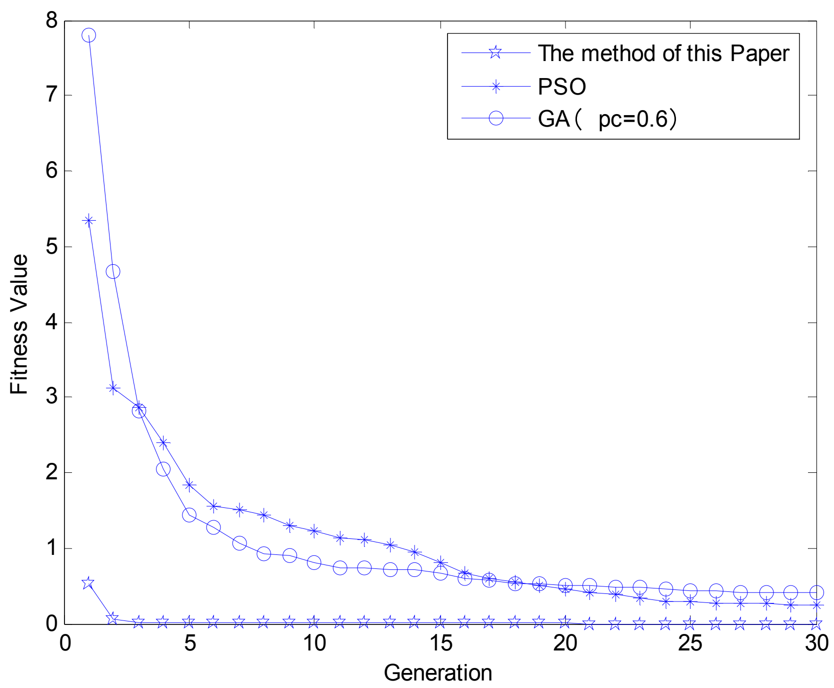

Figure 3. Three-input XOR average fitness value evolution curve comparison chart

4. Conclusion

PSO algorithm, BP algorithm introduces the idea of PSO, proposed an improved particle swarm optimization algorithm, with a three-input XOR function test standard PSO, SGA and improved particle swarm optimization results show that the improved particle swarm optimization algorithm in convergence speed and global search ability is better than PSO, SGA algorithm, to avoid premature and local convergence.

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