$$\lambda_i = \lambda_k \delta_i^{j+1} \quad (11)$$

$$\delta_i^{j+1} = 8\delta_i^j (1-\delta_i^j) - 1 \quad (12)$$

Step 5 Mutation operations: Set the mutated gene as w_i, the following as $w_i^{'} = w_i + \beta(w_i^U - w_i)$ or $w_i^{'} = w_i + \beta(w_i - w_i^L)$, where w_i^U is the upper bound, w_i^L is the lower bound, and β is the chaotic variable that changes in the interval of $(-1,1)$. Mutation operations need to define variation amplitude of $\tilde{\lambda}_k$ at first, and then chaos variables are introduced. For *m* individuals elected to be variated, sort in ascending order of fitness. For the *k t*h individual, variation amplitude of $\tilde{\lambda}_k$ can be chosen as Eq. (13), where $\tilde{\lambda}_0$ is the parameter that controls the disturbance size, and β searches in the interval of $[-\tilde{\lambda}_k, \tilde{\lambda}_k]$.

$$\tilde{\lambda}_k = \tilde{\lambda}_0 \exp((m-k)/m) \quad (13)$$

If satisfies the termination condition, save the optimal solution and stop. Otherwise, select the particles whose adaptation degree is before 50%, supply the others to the population in the feasible solution space randomly, make the population reach the given size of N, and generate a new population G^1. Go to Step 3.

V. The application in multi-dynamic recognition of signals

Consider recognition problems of time-varying signals as the following forms of multi-dynamic system $\tilde{H}(t_1, t_2)$ based on MAPNN.

$$\tilde{H}(t_1,t_2) = \{(t_1 \sin((a_1t_1 + a_2t_2)\pi), t_2 \cos(a_3t_1t_2))\text{;}$$

$$(t_1 \sin((b_1t_1 + b_2t_2)\pi), t_2 \cos(b_3t_1t_2))\text{;}$$

$$(t_1 \sin((c_1t_1 + c_2t_2)\pi), t_2 \cos(c_3t_1t_2\pi)\}$$

where $(t_1, t_2) \in [0,1] \times [0,1]$. a_i, b_i, c_i are parameters of signals, where i can be chosen from 1 to 3. a_1, a_2 change in the interval of $[0.5, 0.7]$ and a_3 changes in the interval of $[1.0, 1.2]$, which build the first class of signals. b_1, b_2 change in the interval of $[0.75, 0.95]$ and b_3 changes in the interval of $[1.2, 1.3]$, which build the second class of signals. c_1, c_2 changes in the interval of $[1.0, 1.2]$ and c_3 changes in the interval of $[1.3, 1.5]$, which build the third class of signals.

Build the training sample set of MAPNN as follows: take 30 groups of values of signal parameters of a_i, b_i, c_i from the intervals defined respectively, and build a dynamic sample set of 90 groups. Select 60 groups as the training set, the other 30 groups as the test set. Suppose the output of the first class of signals be 0.0, the output of the second class of signals be 0.5, and the output of the third class of signals be 1.0. Classify the process signals of MAPNN expressed by Eq. (2), and select the network structure as 2-8-1, of which the number of input nodes is 2, the number of hidden nodes is 8, and the number of output nodes is 1. Select the basis function as Binary 5th order polynomial function, the size of population as 60, the Optimization times as 5000, and error accuracy of learning as 0.05. In contrast, train the network according to the learning algorithm based on gradient descent [1] at the same time. Run 10 times with each algorithm, and classify the 30 samples in the test set with the results. The average training time based on CGA-LMS is 57.63 seconds, and the average correct recognition rate is 90%. The average training time based on gradient descent is 94.02 seconds, and the average correct recognition rate is 83.33%. The results show that the algorithm based on LMS-CGA is workable to train MAPNN, and improved the learning properties of MAPNN greatly.

VI. Conclusion

A train method of MAPNN based on chaos genetic algorithm with lowest mean square algorithm is proposed in the paper. According to the aggregation operation and the mapping mechanism of MAPNN in spatio-temporal dimension signal space, design and analyze the objective function of network training.

The functional optimization problem of MAPNN has been transformed to the problem of multivariate function to solve extreme value. The global optimal solution of network parameters is solved in feasible solution space by using the chaos rail to traverse the search of the CGA, which has reference value on the learning of other machine models and the complex function optimization problems.

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