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A Forecasting Method Based on Online Self-Correcting Single Model RBF Neural Network

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Abstract

In order to enhance the stability of RBF neural network under constant changing conditions, we propose a new scheme of forecasting method based on single model structure. The method can avoid inherent defects of double model structure and improve the network's online self-correcting ability. Self-correcting is realized by continuous online learning and structure adjustment according to the changes of monitoring environment. New samples are used to improve the network approximation precision during work time. The neural network shows remarkable adaptability to slow and quick changing environment from simulation result and the minimum error is only 0.0005 during time 49995s~50005s. According to the simulation of memory optimization, system could adjust the structure of hidden layer adaptively.

Keywords: Forecasting; RBF; Neural network; Self-correcting

1. Introduction

RBF neural network is widely used in diagnosis system [1, 2], system modelling [3, 4] and control system [5, 6]. Most RBF neural network acts as a fixed abstract function for prediction according to a few representative samples, and failed to play out all functions. In order to make the RBF neural network as a forecasting system or soft measurement which can be widely used in production or life, it is necessary to improve the operation mode of RBF neural network, such as self-correcting ability. Ref. [1] researches the double model structure of RBF neural network which includes the offline adjusting structure and

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online weight modifying. This paper proposes an online self-correcting RBF neural network with single model for forecasting. Various kinds of properties are analysed, including the network adaptability, memory consumption and approximation precision. The simulation result shows that it has more advantages than the double model structure.

2. Operation mechanism of the online self-correlating RBF neural network

2.1. Architecture and mechanism of the network

The structure of self-correcting RBF network forecast system is based on dynamic fitting. System trains the network and modifies weight and structure of hidden layer according to the input data and output error. As no sample clustering, the online system breaks the limitation of sample size and RBF neural network become an abstract dynamic function. RBF neural network organization algorithm uses LMS learning algorithm as follow.

$$\begin{cases} b_j(t+1) = b_j(t) - 2\sigma e_j(t) \\ w_{ij}(t+1) = w_{ij}(t) + 2\sigma e_j(t) o_i^{(A)}(t) \end{cases} \tag{1}$$

The corresponding neural network algorithm can be derived by

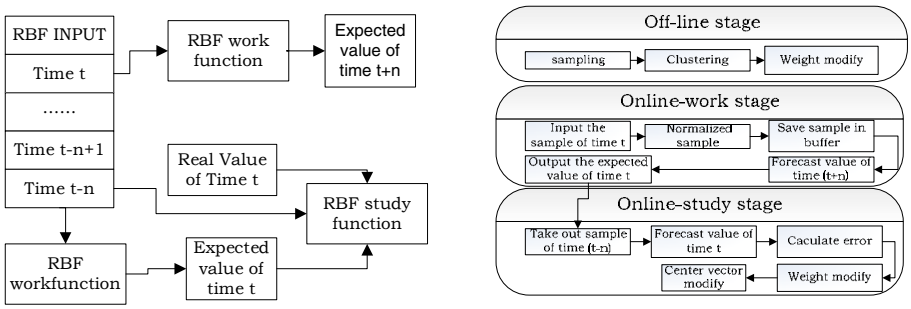
$$O_j(t) = \sum_{i=1}^{H} w_{ij} o_i^{A}(t) - b_j(t) \tag{2}$$

where $O_j(t)$ is output of the jth at time t; $e_j(t)$ is error of the jth; σ is learning rate; $W_{ij}(t)$ is weight between the ith neuron in hidden layer and the j^{et} neuron in output layer; $O_{il}^{(A)}$ is the output of the i^{tch} layer neuron.

If G is Gaussian Function, x^s is the input vector, and $C^{(i)}$ is the centre vector of the ith neuron in hidden layer, the following relationship can be derived.

$$\begin{cases} e_j(t) = O_{dj}(t) - O_j(t) \\ o_i^{(A)}(t) = G(\|x^s(t) - C^{(i)}(t)\|) \end{cases} \tag{3}$$

For online forecast system, the prediction output value O_j (t) and actual value $O_{dj}(t)$ can not be obtained in the meantime. We construct a data buffer to accumulate the historical data and provide samples for learning shown in Fig. 1 (a).



(a) (b)

Fig. 1 The mechanism of the neural network. (a) Data buffer and learning frame; (b) Operation procedure.

Fig. 1(b) describes the procedure of self-correcting RBF neural network. In the offline stage, system trains the network with some representative samples and make sure that the network could meet the minimum requirement. In the Online stage, system will continuously send samples into the data buffer for saving and prediction.

2.2. Online adjustment of the center vectors

During the Online stage, it is difficult to cluster samples and adjust the centre vectors. We present a more concise method for centre vector adjustment. It saves accumulation and derivation, and avoids the hidden layer neurons exceeding too concentration while with a good approximation precision. Assuming that the output layer has only one neuron and e_j (t) is the output error for model simplification, then the centre vector can by derived by

$$C^{(i)}(t+1) = C^{(i)}(t) + \beta o_i^{(A)} e(t) \left| e(t) \right| \left[\left(x^s(t) - C^{(i)}(t) \right) + \alpha \left(st\_C - C^{(i)}(t) \right) \right] \tag{4}$$

Where st_C is the hidden neuron's initial centre vector, (x_s(t)-$C^{(i)}$(t)) could reconstruct hidden layer structures. On contrary, (st_C-$C^{(i)}$(t)) helps hidden layer neurons return to the initial position. The system will reach dynamic balance with the balance coefficient α (0 < α < 1) and the speed coefficient β.

3. Simulation analyzing of the forecasting model

In the following simulation, t represents time, sampling and learning interval is 0.1s, learning rate is 0.1, α is 0.5, and β is 4000. For every sample, the interval time of working and learning is 5s. The following simulations do not include the off-line stage and the error $d_{average}$ is calculated by

$$d_{average} = \frac{\sum_{i=0}^{i=99} \left[e(t - 0.1i) \right]^2}{100} \tag{5}$$

To analysis the performance, the tracking model are build as follow (x, y, z is random).

$$f(x,y,z) = 0.387\sin(x) + 0.86\cos\left[y(z + 0.001t)\right] \tag{6}$$

$$f(x,y,z) = 0.387\sin(x) + 0.86\cos(yz) \tag{7}$$

$$\begin{cases} f(x,y,z) = 0.387\sin(x) + 0.86\cos(yz) & t < 50 \\ f(x,y,z) = 0.387\sin(x) + 0.86\cos\left[y(z+1)\right] & t \geq 50 \end{cases} \tag{8}$$

3.1. Adaptability and the output precision analyzing

Equation (6), (7) is used for simulating slow changes and ideal environment, and Equation (8) is used for simulating environment with quick changes at t=50s. The number of neurons in hidden layer is 400, and the errors of above three cases are shown in Fig. 2(a). In Fig. 2(a), the adverse effects at t = 50s is reduced by self-correcting effectively, and the influence of slow environment changes is negligible.

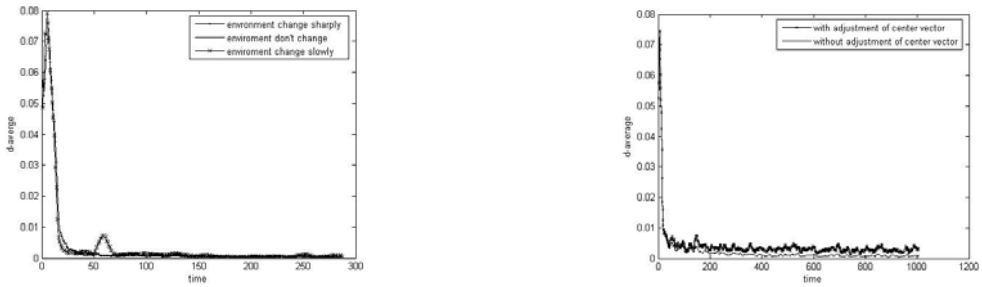


Fig. 2 (a) Performance analyzing of the network. (a) Environment changes and output errors; (b) Output errors with and without adjustment of centre vectors.

The single model of self-correcting RBF neural network is more accurate compared with the double model structure of RBF neural network. This can be proved by the following two aspects.

First, construct two nets with 70 neurons in the hidden layer and fit the Equation (7). Fig. 2(b) reveals the influence of centre vector's adjustment. It can be seen that the precision of the single model of self-correcting RBF neural networks is more accurate than the double structure model of online-net as the structure of hidden layer is not modified which contributes to the approximation precision.

Second, create a net with 120 neurons in hidden layer to track Equation (7), and the simulation results are shown in Table 1.

Table 1. The output error at different times.

time	Max $d_{average}$	Min $d_{average}$
45s<t<55s	0.00420113	0.00333837
495s<t<505s	5.35142E-4	4.49282E-4
4995s<t<5005s	2.71244E-4	1.07924E-4
49995s<t<50005s	6.29738E-5	5.24982E-5

As the RBF neural network revises itself by the real-time sample, the error of fitting decreases gradually and the minimum error during 49955s ~ 50005s is 0.0005. So RBF neural network will implement universal approximation [8] of the curve. In contrast, the off-line net of double model structure is merely trained by limited samples and could not reach very high approximation accuracy.

3.2. Optimization of memory

Generally, neural network occupies lots of memory, and the lack of memory affects the performance of online system seriously. A method is required urgently to dynamically optimize the memory. The Self-correcting net can modify the number of neurons in the hidden layer according to the remaining of memory which make the system run effectively. In simulation, three neural networks were constructed and the tracking model is Equation (7). All neural network have 400 initial neurons, and at time t = 50s, neural network 1 (net1) reduces the number sharply to 100. The number of neuron in hidden layer of neural network 2 (net2) decreases one per second until there are 100 neurons left. Neural network 3 (net3) works as a blank reference, and the number of neuron in hidden layer is unvaried.

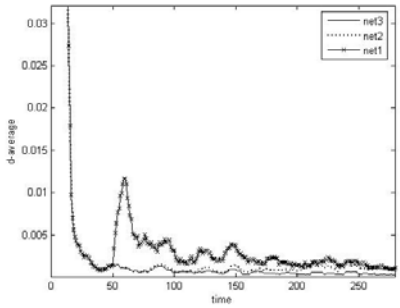


Fig. 3 Error and the number of neuron in hidden layer

In Fig. 3, the simulation result indicates that the sharp decrease of neurons in hidden layer causes a big output error, but the influence could be weaken quickly by self-correcting. Net2 which the number of

neuron in hidden layer decreases slowly has a small effect on the output result that compared with net3. Deleting neurons in the hidden layer could be used to relieve the system pressure of memory.

4. Conclusion

(1) The forecasting method of self-correcting RBF neural net works is adaptive in the environment which changes sharply or slowly.

(2) The self-correcting single model RBF neural network has high approximation precision and a universal approximation to the real curve which it tracks.

(3) The online self-correcting model RBF neural network uses less memory and can be further reduced by deleting neurons in the hidden layer.

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