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Application of RBF Neural Network in Atmospheric Environmental Quality Assessment under Industrial Property Right Structure

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Abstract

Firstly, this paper analyses the structure system of industrial property right under the background of the environment. In the evaluation of atmospheric environmental quality, RBF neural network model is used in the article. Different from BP network, function-connected network realizes the classification of complex patterns by enhancing input patterns. The model is used to study the atmospheric environmental quality of an example. The results show that the application of function-connected network in environmental quality assessment is objective and practical.

Keywords: RBF neural network, environmental quality, assessment

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INTRODUCTION

Air pollution assessment and prediction can not only better understand the dynamic changes of air pollution, provide real-time, systematic and accurate air quality information, but also strengthen the control of environmental pollution and avoid serious pollution incidents. At present, the study of air quality assessment and analysis methods is not limited to index evaluation, principal component analysis, grey system analysis and fuzzy mathematics analysis. A variety of methods for air pollution assessment include artificial neural network method (Feng et al. 2015, Ibarra-Berastegi et al. 2008, Kurt et al. 2008), matter element extension method (Karaca et al. 2006), projection pursuit analysis method and set pair analysis method (Seshagiri 2000). Artificial neural network (ANN) is an artificial intelligence machine that simulates the structure and function of human brain. It has been widely used in image processing, financial market simulation, earthquake prediction and hydroelectric power generation. Compared with other methods, artificial neural network has the ability of self-learning, associative storage and high-speed search for optimal solutions. It is a powerful tool for dealing with non-linear, uncertain and complex problems. At present, the report of urban air pollution assessment and prediction is mainly evaluated by converting it into air pollution index (API). The result is concise and intuitive, which is suitable for expressing the short-term air quality situation and changing trend of the city. As an organic combination of artificial neural network, RBF neural network combines the advantages of two new disciplines and has stronger functions and advantages. It has been well applied in transformer fault diagnosis, exhaust gas detection and classification, especially in solving eigenvectors based on interval classification, clustering and recognition. In this paper, the mapping relationship between pollutant concentration and API is obtained through network modeling of monitoring data from different monitoring points in Beijing in the same year and different dates, so as to realize intelligent evaluation and prediction of monitoring points (Wu and Chow 2004, Yun et al. 2008).

DESIGN OF RBF EVALUATION NEURAL NETWORK ALGORITHMS

Actually, RBF is a three-layer forward network with a single hidden layer. The first layer is the input layer, which is composed of signal source nodes. The second layer is the hidden layer. The number of hidden layer nodes depends on the needs of the problem described. The transformation function of the neuron in the hidden layer, namely the radial basis function, is a non-negative linear function which is radial symmetric and decaying to the center point. It is a local response function. The third layer is the output layer, which is the response to the input mode (García 2009, Lynd

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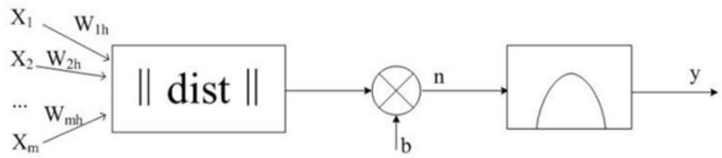

Fig. 1. The Diagram Of RBF Neural Network Structure

1987, Mao and Huang 2005). The input layer only plays the role of transmitting signals, and the connection weight between the input layer and the hidden layer can be regarded as the connection with a value of 1. The tasks completed by the output layer and the hidden layer are different, so their learning strategies are different. The output layer adjusts the linear weight and adopts the linear optimization strategy, so the learning speed is higher. The hidden layer adjusts the parameters of the activation function and adopts the nonlinear optimization strategy, so the learning speed is lower (Başaran 2016).

The basic idea of RBF neural network is that RBF is used as the "basis" of the hidden unit to form the hidden layer space. The hidden layer transforms the input vector, so as to transform the input data of the low-dimensional mode into the high-dimensional space, and make the linear inseparability problem in the low-dimensional space linearly separable in the high-dimensional space. Specifically, the hidden unit of RBF is used to form the hidden layer space, so that the input vector can be directly mapped to the hidden space. When the center of RBF is determined, the mapping relationship is determined. The mapping from hidden layer space to output space is linear, that is, the network output is the linear weighted sum of unit output, and the weight here is tunable parameter of the network (Boldrin and Levine 2008).

The activation function of the radial basis function takes the distance between the input vector and the weight vector ||dist|| as the independent variable. The general expression of activation function of radial basis network is as shown by equation (1).

$$R(\|dist\|) = e^{(-\|dist\|^2)} \quad (1)$$

In this formula, the obtained R is the value of the hidden layer neuron(HLN) (Er et al. 2002).

The radial basis network transfer function takes the distance between the input vector and the threshold vector || X-Cj || as the independent variable, where || X -Cj || is obtained by the product of the input vector and the row vector of the weighted matrix C. Here, C is the central parameter of each neuron in the hidden layer. The size is the number of hidden neurons * number of visible layer cells. Furthermore, each hidden neuron center parameter C corresponds to a width vector D, so that different input information can be reflected by different hidden neurons to the greatest extent. As the distance between the weight and the input vector decreases, the network output is increasing. When the input vector and the weight vector are consistent, the neuron output is 1 (Er et al. 2005, Yingwei et al. 1998). In **Fig. 1**, b is the threshold, which is used to adjust the sensitivity of neurons. The generalized regression neural network can be established by using radial basis neurons and linear neurons. The neural network is suitable for function approximation. Radial basis function and competitive neuron can establish probabilistic neural network, which is suitable for solving classification problems.

FUNCTIONAL CONNECTION MODEL AND ITS TRAINING ALGORITHMS

Introduction of Training Algorithms

X =[x1 , x2 , x3 , … , xd] , is a d dimensional input vector; Φ(X) means the connection of the function, which is used to transform input vectors in X space to higher dimensional ξ space, ξ=[ξ1, ξ2, …, ξr] (r >d), so as to enhance the expression of original patterns, the expression is as follows:

$$\xi = \Phi(X) \quad (2)$$

Φ(X) is a set of non-linear function, Φ(X)=[Φ1(X), Φ2(X), … , Φr(X)] T, t can have many choices, and its basic requirement is to ensure that the enhanced vector is linearly independent. For example, Φ(X) can be selected as a subset of the orthogonal function system, such as

$$\xi i = \Phi i(X) = x, \sin(\pi x), \cos(\pi x), \sin(2\pi x) \dots \quad (3)$$

In order to enhance the expression of input modes, a second-order outer product enhancement scheme can also be used. In this way, the hyper plane ofξ space is equivalent to the quadratic hyper surface in the original X space, and the complexity of the divisible region can be enhanced (Mahanty and Gupta 2004).

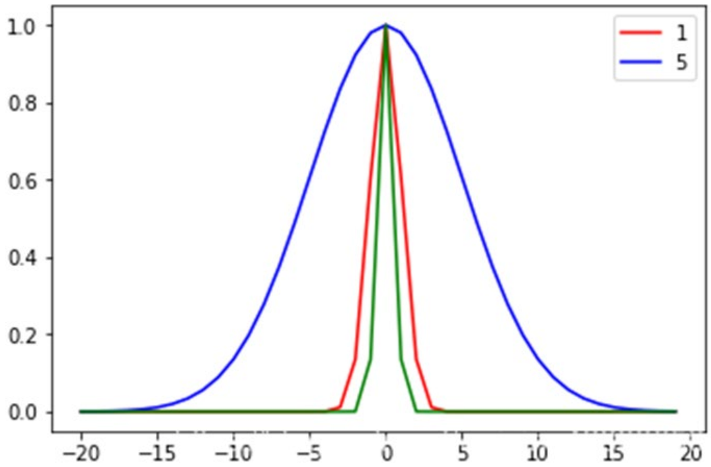

Fig. 2. Different δ value effect in the training speed

Table 1. Standard data input and output according to the RBF neural network

Input Vector					Output Vector			
Indicators	SO_2	NO_X	TSP	Dust				
Level I	0.002	0.016	0.02	3.4	0.9	0.1	0.1	0.1
Level II	0.02	0.05	0.15	6.8	0.1	0.9	0.1	0.1
Level III	0.06	0.1	0.3	10.2	0.1	0.1	0.9	0.1
Level IV	0.1	0.15	0.5	13.6	0.1	0.1	0.1	0.9

In principle, as long as the appropriate connection function is selected, the network can always be connected by a single-layer function to achieve the required classification function.

The distance from axis to center is expressed by radius R. As shown in **Fig. 2**, we find that when the distance is equal to 0, the radial basis function is equal to 1. The farther the distance is, the faster the attenuation is. The parameters of Gauss radial basis function are called the arrival rate or the speed at which the function falls to zero in support vector machines. Red $\delta = 1$, blue $\delta = 5$, green $\delta = 0.5$, we find that the smaller the arrival rate, the narrower it is.

The training algorithm of functional connected neural network is as follows:

Before training RBF network, input vector X and target vector T need to be given. The purpose of training is to obtain the weights of W1, B1, W2 and B2 between the first and second layers.

The training of the whole network is divided into two steps. The first part is unsupervised learning, seeking W1 and B1. The second step is supervised learning for W2 and B2.

The network is trained from 0 neurons, and the network automatically increases neurons by checking the output errors. Each cycle, repeat the process until the error meets the requirements. Therefore, RBF network has the characteristics of self-adapting structure determination and independent output of initial weights.

RBF network has a parameter called spread. When creating RBF network in MATLAB, it must be set beforehand. Its default value is 1.

The larger the neural network spreads, the smoother the function fitting, but the larger the approximation error, the more hidden neurons needed, and the larger the calculation.

The smaller the spreads, the more accurate the function approximation will be, but the approximation process will not be smooth, the network performance will be poor, and there will be Over-adaptation phenomenon.

Different spreads should be tried in the specific operations in the neural network. Spread is so large that the input range of neuron response can cover a large enough area, but also not too large, so that each neuron has overlapping input vector response area.

From the above training process, it can be seen that the weight training process is relatively simple and requires less time. **Table 1** shows the standard data input and output according to the RBF neural network.

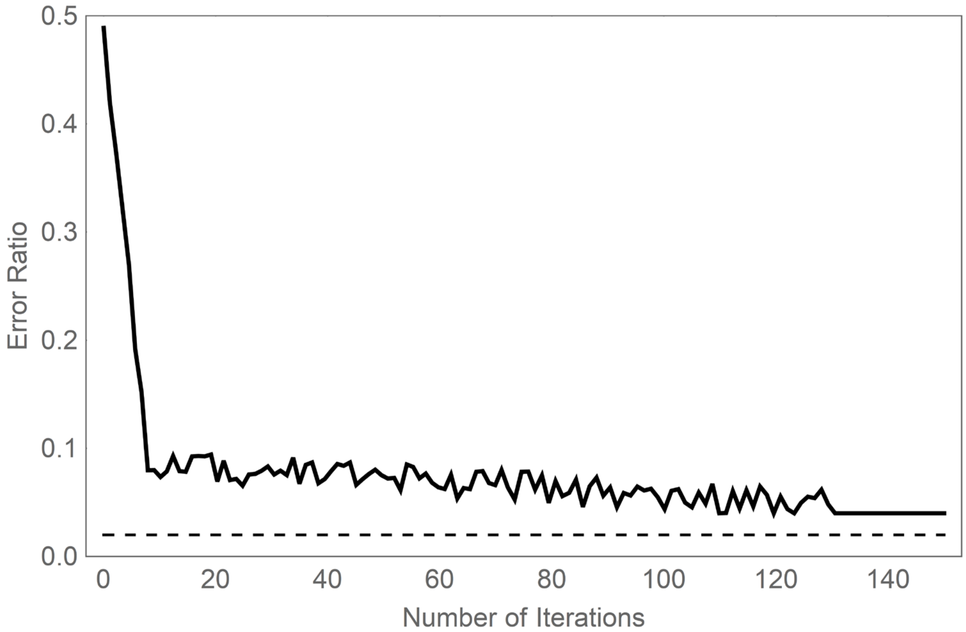

Fig. 3. Error ratio of RBF neural network

Industrial Property Right Structure

The industrial scale structure is reflected by the proportion of the output value of large, medium and small enterprises to the total output value of industry. Enterprises of different sizes have different impacts on economy, society and environment. For example, large enterprises have strong R&D capability, small enterprises have strong ability to absorb employment, large enterprises have strong risk resistance, small enterprises have greater flexibility, and large enterprises have relatively easy environmental supervision. Therefore, the proportion of enterprises of different sizes in industry and their changes are an important focus of industrial policy (Flyer et al. 2016, Li and Verma 2016).

Grey relational analysis method makes up for the shortcomings caused by using mathematical statistics method for system analysis. It is also applicable to the number of samples and the regularity of samples. The basic idea of grey relational analysis is to judge whether the sequence curves are closely related according to the similarity of geometric shapes. The closer the curve is, the greater the correlation between the corresponding sequences, and vice versa. The significance of grey relational degree analysis is that in the process of system development, if the two factors change in the same situation, that is, the degree of synchronous change is higher, the two factors can be considered to be more relevant; on the contrary, the degree of correlation between the two factors is smaller. Therefore, the grey relational degree analysis provides a quantitative measure for the development and change of a system, which is very suitable for dynamic (Dynam, ic) process analysis. The basic object of grey relational analysis is data series, which is divided into mother series and sub-series. Usually, the mother number is listed as the reference data column, and the child number is listed as the comparative data column.

By means of grey prediction and normalization, the pollution data in enterprises can be reduced by other factors, and the uniqueness of the impact of industrial property right structure on environmental pollution can be guaranteed.

Experimental Simulation

According to the above model and training algorithm, a computer program is compiled and applied to the actual atmospheric environmental quality assessment. The data are shown in **Table 2**.

The settings are as follows: the maximum training times are 500, the training accuracy is 0.02, the training speed is 0.03, and the training speed here is the minimum training speed. The maximum training speed is 0.09. The error rate drops sharply at the beginning of training and reaches 0.1 at the eighth step. Finally, the training accuracy of 0.02 is achieved through continuous fine-tuning.

After the above training, a function-connected neural network with complex correspondence relationship between evaluation index and atmospheric environmental quality grade can be established.

Table 2. Neural Network Training Samples

Number	SO_2	NO_2	PM_{10}	Pollution Level
1	0.003	0.003	0.102	I
2	0.048	0.015	0.106	I
3	0.02	0.008	0.112	I
4	0.002	0.001	0.101	I
5	0.05	0.047	0.15	I
6	0.064	0.063	0.146	I
7	0.054	0.048	0.186	II
8	0.091	0.07	0.199	II
9	0.035	0.015	0.17	II
10	0.086	0.072	0.211	II
11	0.196	0.072	0.211	II
12	0.088	0.058	0.215	II
13	0.187	0.082	0.301	III
14	0.21	0.066	0.263	III
15	0.205	0.68	0.284	III
16	0.225	0.091	0.342	III

Table 3. The result of the RBF neural networks

Input Vector					Neural Network Calculation Results				Rating
Sample	SO_2	NO_X	TSP	Dust					
Average	0.086	0.026	0.44	12.6	0.0993	0.0988	0.4035	0.8721	IV
Industrial Zone	0.077	0.018	0.41	16	0.1046	0.0971	0.8563	0.1465	III
Residential Areas	0.134	0.031	0.431	16.5	0.0956	0.1224	0.1109	0.8921	IV
Transport Area	0.093	0.056	0.962	9.8	0.0964	0.1046	0.0977	0.8977	IV
Scenic Spot	0.46	0.012	0.18	4.8	0.3279	0.5204	0.2035	0.0959	II
Sterile Area	0.022	0.006	0.231	3.8	0.1675	0.8248	0.168	0.0997	II
Spring	0.11	0.038	0.551	14.3	0.1265	0.0993	0.274	0.7266	IV
Summer	0.093	0.036	0.514	16.2	0.1012	0.0976	0.1278	0.8751	IV
Autumn	0.057	0.014	0.35	9.6	0.0999	0.115	0.8876	0.0974	III
Winter	0.085	0.014	0.34	10.2	0.097	0.0956	0.8958	0.1039	III

Ten sets of measured data of air environmental quality pollution indicators were selected as the actual samples, and the 10 sets of measured samples were identified by using the above-mentioned trained function-connected neural network. The results are shown in **Table 2**.

RBF neural network not only has the advantages of general neural network, such as multi-dimensional non-linear mapping ability, generalization ability, parallel information processing ability, etc., but also has the advantages of BF neural network.

Strong clustering analysis ability, simple learning algorithm and other advantages; Radial Basis Function (RBF) neural network is a kind of forward network L with good performance, which can identify and model almost all systems by using traditional interpolation technology in multi-dimensional space. It not only has arbitrary approximation performance and optimal approximation performance in theory, but also has many advantages in application. Compared with the neural network with Sigmo ID function as activation function, the speed of the algorithm is much faster than that of the general BP algorithm.

RBF neural network is not only the optimal network in forward network in theory, but also the learning method avoids the problem of local optimum. It has been proved that a RBF network can approximate any non-linear function with arbitrary precision and has the best function approximation ability when there are enough hidden layer nodes. In addition, it has fast convergence speed and strong anti-noise and repair ability.

In theory, RBF network, like BP network, can approximate any non-linear function with arbitrary accuracy. However, their approximation performance is different due to the different excitation functions they use. Poggio and Girosi have proved that RBF network is the best approximation of continuous functions, while BP network is not. The Sigmoid function used in BP network has global characteristics. It affects the output value of each node in a large range of input values, and the excitation functions overlap in a large range of input values, so the training process of BP network is very long. In addition, because of the inherent characteristics of BP algorithm, it is impossible to fundamentally avoid the problem that BP network is easy to fall into local minimum, and the determination of the number of hidden nodes in BP network depends on experience and trial-and-error, so it is difficult to get the optimal network. RBF network with local excitation function overcomes the above shortcomings to a great extent. RBF not only has good generalization ability, but also has non-zero excitation value for each input value, so only a few nodes and weights need to be changed. The learning speed can be thousands of times faster than the usual BP algorithm, and it is easy to adapt to new data. The number of hidden layer nodes is also determined in the training process, and its convergence is easier to guarantee than that of BP network, so the optimal solution can be obtained.

CONCLUSION

The application of RBF neural network method in atmospheric environmental quality assessment has the advantages of strong fault tolerance, simple calculation, objective evaluation and wide practical range. In this paper, a function-connected neural network is used to recognize complex patterns by enhancing input patterns.

Compared with the traditional forward multi-layer neural network, it has the characteristics of simple structure and fast training speed. By choosing the appropriate pattern enhancement function, the network can always be connected with a single-layer function to complete the required recognition function. The application results show that the method comprehensively evaluates the impact of various pollution indicators, and shows the superiority and rationality of the function-connected neural network method.

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