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Research on the Nonlinear Traffic Flow Time Sequence Prediction Model

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Abstract

This paper proposes a non-linear traffic flow time sequence prediction model aiming at the periodic and stochastic characteristics of the traffic flow. First, one-dimension traffic flow time sequence data are transformed to multi-dimension time sequence. Then the RBF neural network which has strong nonlinear prediction capability is applied to model. Finally the simulation experiment is used to testify to the model. The results of the simulation prove the prediction accuracy of the model with RBF neural traffic flow time sequence prediction model is much higher than the traditional one and the prediction results can be utilized in the practical traffic management. The results show that the nonlinear traffic flow time series forecasting model with nonlinear, non-stationary characteristics of different period randomness, chaos and uncertainty. The results of this study to forecast short-term traffic flow have certain theoretical and practical significance.

Keywords: *traffic flow, rbf neural network, time sequence, non-linear*

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1. Introduction

With the rapid urbanization process in China, the traffic flow is increasing daily. Due to the latency of urban infrastructure construction and urban management, traffic congestion is increasingly worsened. In order to effectively plan and manage the traffic, after reasonable rules of the road and the expansion of the road well, or become increasingly weak. Therefore, the prediction and control of the traffic flow are more and more urgent [1-5].

The short-time traffic flow has a strong relationship with the time and it has uncertain and nonlinear characteristics. Not easy to find regularity, the method can be applied; but it's a typical time sequence prediction issue for the short-time traffic flow prediction. The time sequence of prediction method is that Study predict the target and the time course of evolution relationships, according to the statistical regularity structure fitting the best mathematical model of X (t), and concentrated to the time-series information, to simplify the representation of the time sequence, and with the best mathematical model for future prediction method.By generalizing the previous researches, one-dimension regression prediction model, multi-dimension regression and artificial intelligence algorithm are most common [6-8].

Because of the uncertainty and strong nonlinearity of the short-time traffic flow, the prediction of the one-dimension and multi-dimension model is based on linear time sequence. However, the obvious nonlinear characteristic of the traffic flow causes the prediction performance unsatisfactory [9-14]. Often cause errors, bring great convenience to people's travel and traffic safety. Over time, scholars have found, and the artificial intelligence method is a new machine learning method which can accurately describe the mapping relationship among factors. The history of the development of artificial intelligence is linked to the history of the development of computer science and technology. "Artificial intelligence" term was originally proposed in 1956 on the Dartmouth Society. Since then, researchers have developed a number of principles and theories; also will expand the concept of artificial intelligence. Artificial intelligence is infinitely approaches the non-linear between the input and output factors, which are regarded as a very good model and method to predict nonlinear model [15-24]. Uncertainty information processing is a class of important research in the field of artificial intelligence research. In order to deal with the uncertainty of information, people develop a variety of mathematical tools and methods. Such as fuzzy set theory, Bayesian belief networks, DS evidence theory and rough set theory. These theories and methods are developed to deal with

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the uncertainty information. They also provide strong support for the current data mining and knowledge discovery.

This paper proposes a nonlinear traffic flow time sequence prediction model aiming at the periodic and stochastic characteristics of the traffic flow, which applies RBF neural network as modeling method and is testified by the simulation experiment.

2. RBF Neural Networks

2.1. RBF Neural Network Algorithm

There are three tier in the RBF neural network, including one input tier, one hidden tier and one output tier. The structure of the RBF neural network is as shown in Figure 1 [7].

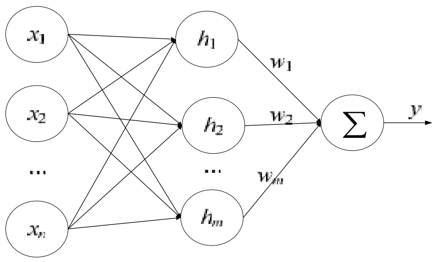

Figure 1. RBF Neural Network Prediction Model Structure

Assuming the input dimension of the RBF neural network is n, the amounts of the neural units in hidden tier is m, the output dimension is p, the RBF neural network computation process is as follows.

(1) Nonlinear transfer from input tier to hidden tier

The radial basis functions are used as the transfer function between input tier and hidden tier. Radial basis function is a symmetry scalar function along the radial direction, which represents the monotonic distance function between any point x in the space and some central point c_i indicating by $¤(\| x-c_j \|, \pm_j)$. It expressed as follows:

$$h_j(x) = ¤(\| x-c_j \|, \pm_j) = \exp(-\frac{\| x-c_j \| 2}{2\pm_j^2}) \quad (1)$$

In the equation, $¤(\cdot)$ is the transformation function in the units of hidden tier, $\| \ \|$ is Euclidean paradigm, j is the amount of neural units in the hidden tier, c_j is the central of jth node in the RBF neural network hidden tier, $\pm_j$ is the width of the nodes in the RBF neural network hidden tier.

(2) The linear combination from the hidden tier to output tier

In RBF neural network, the transfer from hidden space to output space is via sum operation. At this time, the connection weights between the hidden tier and output tier can be adjusted. The adjust function is shown in Equation (2).

$$f(x) = \sum_{j=1}^{m} h_j(x) w_j \quad (2)$$

In the equation, w_j represents the connection weight between j th neural unit in hidden tier and output tier.

The performance index in RBF neural network is illustrated in Equation (3).

$$E = \sum_{i=1}^{p} (y_i^{'} - f(x_i))^2 \tag{3}$$

In the equation, $f(x_i)$ is the output of the RBF neural network, $y_i^{'}$ is the actual output of the training sample, E is the mean square error between these two outputs.

During the training and leaning, if the mean square error E is too large, the penalty factor is introduced to adjust the parameter to make the approaching performance of the RBF function better. In Equation (3) a term of penalty factor is added. At this time, the performance index can be represented as:

$$C = \sum_{i=1}^{p} (y_i^{'} - f(xi))2 + \sum_{i=1}^{m} \text{a}\ jw_j^2 \tag{4}$$

In the expression, a is introduced a penalty factor.

The mapping relationship of the RBF neural network is expressed in the mathematical equation as Equation (5).

$$f(x) = \sum_{j=1}^{m} h_j(x)x_j = \sum_{j=1}^{m} (-\frac{\| x - c_j \| 2}{2\pm_j^2})w_j \tag{5}$$

2.2. RBF Neural Network Short-time Traffic Flow Prediction

According to the previous researches, the traffic flow of some specific time in the urban traffic network closely related to the traffic road network, also related to the previous traffic in the previous a few hours [8]. Thus, the short-time traffic flow model can be built according to the traffic data in the previous hours and then the model can be used to predict the traffic flow.

Assuming the traffic flow at time t in the road section i is $v_i(t)$, and then traffic flow at time $t-1$ is $v_i(t-1)$.

When comes to specific research process, the traffic flows in the previous s time periods are used to predict the traffic flow at some time in the future. $v_i(t), v_i(t-1), \cdots, v_i(t-s)$ are the input of RBF neural network and $v_i(t+1)$ is the output of the RBF neural network. The detailed steps are as follows:

(1) The traffic flow amounts of the previous 5 time points are standardized and the data normalized to the range [0, 1];

(2) After multiple times experiments, the traffic flow data of the pervious 5 time points of the prediction points affects the traffic flow of the prediction point greatly. Based on the phenomenon, the input tier of the RBF neural network can be designed to 5 nodes. The nodes in the hidden tier can be determined by heuristic algorithm. Finally the nodes in the hidden tier can be determined as 11 and output tier is 1 which represents current traffic flow.

(3) RBF neural network learning and training. The collected traffic data can be divided into training set and test set. The training set is used to train the RBF neural network to adjust the three key parameters in the RBF neural network. When the output errors of the RBF neural network are less than set value, the training is ended. The optimal parameters c_j, $\pm_j$ and w_j are stored in the network.

(4) The trained RBF neural network is applied to predict the short-time traffic flow.

3. Simulation Experiment
3.1. Traffic Flow Data
The traffic flow data is collected from some road in the city of Zhengzhou in China. The data is collect every 10 minutes and totally 650 data are collected in Figure 2. All of these data are divided into training set and test set. The previous 550 data are used to build RBF neural network prediction traffic flow model and the later 100 data are used to testify the model.

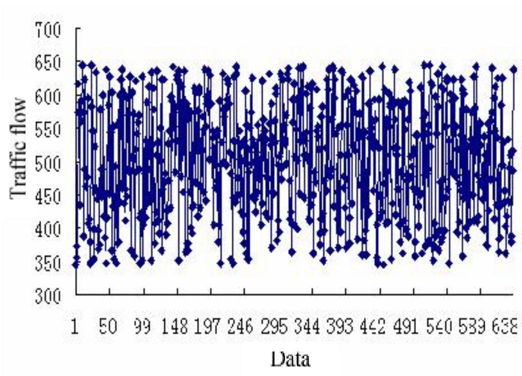

Figure 2. The Original Traffic Flow

3.2. Data Standardized Process
The collected traffic flow original data show some periodic characteristic in Figure 2, however the change amplitudes is very obvious. There are two effects for the RBF neural network model. First, if the differences among the data of the sets are too big, they will affect the learning speed and the accuracy of the prediction. Second, RBF neural network is sensitive for the data in the rage [0 1] and the prediction accuracy is relatively high. Therefore, in the experiment process, the traffic data should be standardized and the normalized equation is as follows.

$$x_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{6}$$

In the equation, x_i is the standardized value of the traffic flow; x_i is the original traffic flow data; $\max(x)$ and $\min(x)$ are the maximum and minimum values respectively in the traffic flow data.

The collected traffic data are standardized by Equation (6) and all of the data are normalized to the range [0 1]. The detailed results are shown in Figure 3.

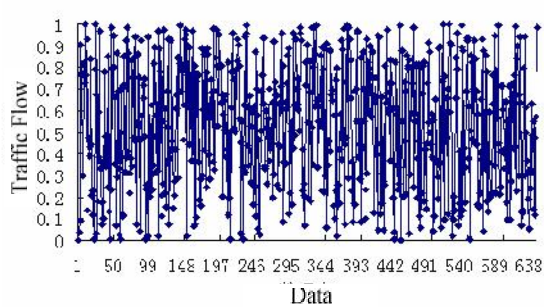

Figure 3. Standardized Results of the Traffic Flow Original Data

3.3. Traffic Flow Prediction

The standardized data are classified. The previous 550 data are used as a training set, the later 100 data are used as test set. Then the training set is inputted into RBF to learn. The previous 5 data is used to predict the following data. The training times are set to 5000. After 3892 times of training, the output errors are less than previous set 0.001, the network stops to train. The optimal parameters c_j , $\pm_j$ and w_j are attained and stored in the network.

The RBF neural network model which meets the training requirements is used to predict the test set. In order to simplify the comparison, the output results are anti-normalized and the real values of the traffic flow are attained. The anti-normalized equation is below.

$$x_i = x_i \times (\max(x) - \min(x)) + \min(x) \tag{7}$$

The one-dimension time sequence model is used to compare with the proposed RBF neural network prediction model. The output results of these two models are shown in Figure 4 and 5 respectively.

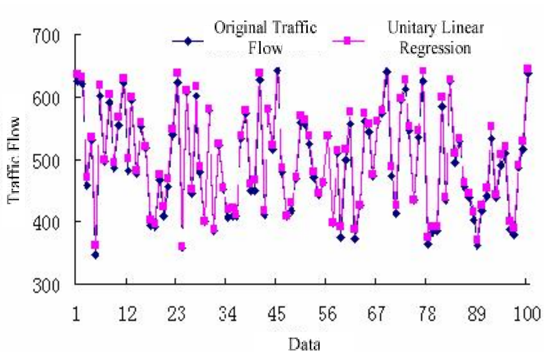

Figure 4. Unitary Linear Traffic Flow Prediction Results

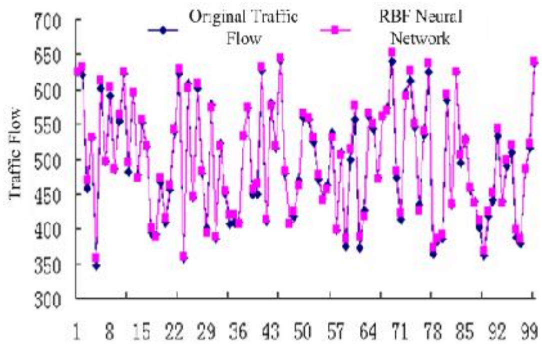

Figure 5. RBF Neural Network Traffic Prediction Results

The prediction accuracy of the RBF neural network is close to the original traffic data and better than unitary regression model in Figure 4 and 5. The RBF neural network has strong nonlinear approaching capability for nonlinear traffic flow data due to it's a kind of intelligent machine algorithm. This paper proposes a nonlinear traffic flow time sequence prediction model aiming at the periodic and stochastic characteristics of the traffic flow, which applies RBF neural network as modeling method and is testified by simulation experiment. Thus it can reflect the flow change while unitary regression model is a model based on linear data time sequence prediction model. Therefore, using linear regression model to predict nonlinear model can't reflect the change and it will cause large errors and low accuracy.

3.4. Prediction Accuracy Comparison

In order to better analyze the accuracy of the traffic flow prediction, the mean absolute percentage error and root mean square error are used to evaluate the prediction performance.

The mean absolute percentage error (MAPE) of the traffic flows.

$$MAPE = \frac{1}{k}\sum_{i=1}^{k}\left|\frac{x_i - x_i}{x_i}\right| \times 100\% \tag{8}$$

(2) The mean square errors (MSE) of the traffic flows

$$MSE = \sqrt{\frac{1}{k}\sum_{i=1}^{k}(\hat{x}_i - x)^2} \tag{9}$$

In the equation, k is the prediction sample of the traffic flows, x_i is the observation value of the traffic flow, and x_i is the prediction value by the prediction model. The less the MAPE and MSE are, the higher the prediction accuracy of the model is.

This paper proposes a nonlinear traffic flow time sequence prediction model aiming at the periodic and stochastic characteristics of the traffic flow, which applies RBF neural network as modeling method and is testified by simulation experiment.

The comprehensive predictive of the two models are shown in Table 1. The advantages of using RBF neural network to predict the traffic flow are illustrated in two aspects compared with unitary regression model.

(1) The traffic flow prediction accuracy. The prediction accuracy of RBF neural network is higher than unitary regression model from the comparison of MAPE and MSE in Table 1, which is realistic.

(2) Model generalization capability. The RBF neural network has more stable prediction performance. Even under the situation of large fitting errors, the prediction performance is relatively stable.

Table 1. Prediction Accuracy of each Model

Model	MAPE	mse
Unitary regression model	15.36%	25.987
RBF neural network model	8.38%	6.233

4. Conclusion

The traffic flows are affected by several factors with the periodic, random and nonlinear characteristics. The traditional linear prediction model fails to accurately predict the complex and volatile traffic flow. This paper proposes a nonlinear traffic flow time sequence prediction model based on RBF neural networks. The simulation experiment proves the RBF neural network can improve the prediction accuracy and accurately describe the traffic flow change characteristics compared with unitary regression model. Furthermore the prediction results can be applied to manage the practical traffic.

This paper proposes a non-linear traffic flow time sequence prediction model aiming at the periodic and stochastic characteristics of the traffic flow. First, the one-dimension traffic flow time sequence data is transformed to multi-dimension time sequence. Then the RBF neural network which has strong nonlinear prediction capability is applied to model. Finally the simulation experiment is used to testify the model. The results of the simulation prove the prediction accuracy of the model with RBF neural traffic flow time sequence prediction model is much higher than the traditional one and the prediction results can be utilized in the practical traffic management.

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