

Based on Wavelet Analysis—Fuzzy Neural Network Real Time Traffic Flow Prediction

Tian Fu and Zhen Wang

Abstract This paper analyses the advantages and disadvantages of Prediction Model of wavelet analysis and fuzzy neural network model in real-time traffic prediction, proposes the traffic flow forecasting model based on wavelet analysis and fuzzy neural networks, uses the frequency components of the model of traffic flow time series for forecasting and finally induces the forecast results. Finally, it verifies the effectiveness of traffic simulation data validation model.

Keywords Wavelet analysis · Fuzzy neural network · Component · ANFIS · Forecast model

1 Overview

With China's rapid economic growth and urbanization, the urban traffic problems have been more serious. The ways of using the Intelligent Transportation Systems (ITS) and effectively solving the traffic congestion has become an important issue of sustainable urban development. So how to finish accurate real-time traffic flow forecasting is the key technology to realize ITS. As the traffic flow with highly non-linear characteristics, domestic and foreign researchers use artificial neural network for nonlinear prediction and achieved certain results [1, 2]. But because the artificial neural network is not unique, it can not meet the demand of the forecast of traffic flow.

Wavelet transform is a time-frequency analysis method. Wavelet analysis can make the stable and random separation of the traffic flow information according to the different frequency components of the data, then the characteristics to be processing and analysis, which can achieve the purpose to improve traffic flow

T. Fu · Z. Wang (✉)
Hainan College of Software Technology, Qionghai, Hainan, China
e-mail: 490345452@qq.com

T. Fu
e-mail: fu-tian@163.com

prediction accuracy [3–5]. Adaptive neural fuzzy inference system (adaptive neuro-fuzzy inference system, ANFI), with artificial neural network self-learning function and fuzzy system inference and decision function, has been used in many fields [6–8]. In this paper, the wavelet analysis and adaptive neural network simulation system (ANFIS) are studied, and the combined model is applied to real-time traffic prediction. Because the combination has the characteristics of self adaptation and self adjustment, it can predict the traffic time series well.

2 Model Prediction Theory

First to obtain the traffic flow data with Mallat wavelet transform method for several resolution decomposition of different frequency signal decomposition, then the decomposition sequences by Mallat space reconstruction, dimension calculation, then use ANFIS model is trained, then ANFIS according to the decomposition sequence component prediction sample results. Finally, the prediction samples each component of the synthesis of the final forecasting results are obtained.

Step 1: Firstly, using wavelet transform Mallat algorithm (i.e. a sequence of discrete wavelet transform algorithm) on the traffic flow time series decomposition, the algorithm is as follows:

$$\begin{cases} c_{i+1} = Hc_i \\ d_{i+1} = Gc_i \end{cases}, i = 0, 1, \dots, I \quad (1)$$

In the formula, H is the low frequency component operator and G is the high frequency component operator; c_i and d_i , respectively, as the original signal in the resolution of the approximation signal and the details of the 2^{-i} signal; and the I is the maximum decomposition level.

c_0 is defined as the original signal L, through the algorithm (1) can be decomposed into $x_1, x_2, x_3, \dots, x_j$ and c_i , each layer of the details of the signal and the approximation signal is the adjacent frequency of the adjacent components of the original signal L.

Step 2: The decomposition sequence of the use of Mallat reconstruction algorithm for space reconstruction, the specific algorithm is as follows:

$$C_i = H^* C_{i+1} + G^* D_{i+1}, i = I, I-1, \dots, 1, 0 \quad (2)$$

In the formula: H^* and G^* are the conjugate transpose matrix H and G.

The reconstruction algorithm (2) of the wavelet decomposition of signal reconstruction can increase the signal points, $d_1, d_2, d_3, \dots, d_l$ and C_l are reconstructed, the reconstructed signal D_1, D_2, \dots, D_l and C_l have consistent points with the original signal L and

$$X = D_1 + D_2 + \dots + D_l + C_l \tag{3}$$

Step 3: The component dimension of the component signal is calculated, and the G-P method is used to reconstruct the phase space, and the distance between the Y_i and Y_j is less than R:

$$C(r) = \frac{1}{N_R^2} \sum_{i=1}^{N_R} \sum_{j=1}^{N_R} H(r - \|y_i - y_j\|) \tag{4}$$

Based on the Takens theorem, the phase space dimension m is determined, and then the time series can be predicted by using the M theorem.

Step 4: The ANFIS model is established, and then the ANFIS model is trained by using the component signals, and the ANFIS is used to predict the sample data. Finally, the final prediction results are obtained. ANFIS is a kind of structure of fuzzy system and neural network, Its regular form is:

$$y_n = \sum_{j=1}^m a_j y_{nj} / \sum_{j=1}^m a_j = \sum_{j=1}^m \bar{a}_j y_{nj} \tag{5}$$

In the formula: $n = 1, 2, \dots, k$, according to the T-S model, can be designed as shown in Fig. 1 the ANFIS network structure, the network is a total of six layers.

Each node of the first layer is wholly intact to input variables passed to the next layer, so it is

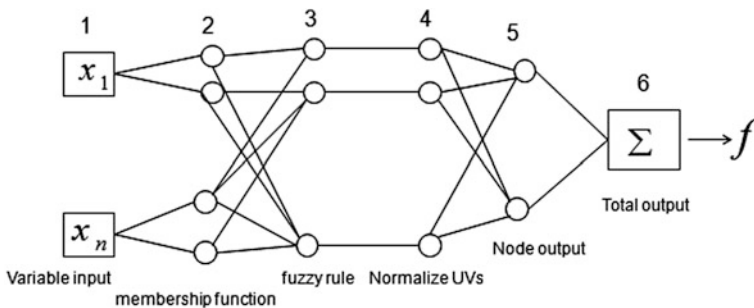


Fig. 1 Structure of ANFIS

$$f_i^{(1)} = x_i \quad (6)$$

In the formula: $i = 1, 2, \dots, n$, represents the sequence of the input nodes in the input layer.

After the fuzzy processing of second layers, the input variables are obtained respectively corresponding to the degree of membership of the fuzzy subset.

$$f_{u_i}^{(2)} = u_i^m(x_i) \quad (7)$$

In the formula: $m = 1, 2, \dots, u_i$, $i = 1, 2, \dots, n$; u_i is fuzzy partition number for x_i .

The third layer is the fuzzy rule base, each node of this layer represents a fuzzy rule, and its function is to calculate the applicability of each rule. The output of this layer is

$$f_j^{(3)} = \min \left\{ f_{1s_{1j}}^{(2)}, f_{2s_{2j}}^{(2)}, \dots, f_{ns_{mj}}^{(2)} \right\} \quad (8)$$

$$j = 1, 2, \dots, m \quad m = \prod_{i=1}^n m_i$$

The number of nodes in the fourth layer is the same as the third layer, which is the normalized calculation. The output of this layer is

$$f_j^{(4)} = f_j^{(3)} / \sum_{j=1}^m f_j^{(3)} \quad (9)$$

Each node of the fifth layer is an adaptive node with a node function. The output of this layer is

$$f_k^{(5)} = \sum_{j=1}^m y_{kj} f_j^{(4)} \quad (10)$$

In the formula: Parameter $\{w_i\}$ in y_{kj} is the parameter set of the node.

The sixth layer is the output layer, which calculates the sum of all the transmitted signals.

$$f^{(6)} = \sum_{k=1}^r f_k^{(5)} \quad (11)$$

For the linear part of the ANFIS output, the least square method is used to identify the linear parameters, which is based on the formula (5) and the formula (10).

$$f_k^{(5)} = \sum_{j=1}^m \left[\sum_{i=1}^n \left(x_{ij} f_j^{(4)} w_{ji}^k \right) + f_j^{(4)} w_{j0}^k \right] \tag{12}$$

$i = 1, 2, \dots, n; j = 1, 2, \dots, m; k = 1, 2, \dots, r$. By the formula (12), it is a linear function of the linear set $\{w_{ji}^k, w_{j0}^k\}$, which can be identified by the least square method.

3 Urban Traffic Flow Time Series Prediction

This article refers to a road of the city within 2 h of traffic flow monitoring data simulation. First, the adverse events are screened out from the data, such as weather, road maintenance, traffic accidents, and others eliminate unfavorable time factors. Then the Daubechies wavelet analysis is used to deal with the time sequence. The fractal dimension value is 3.6, and the dimension of the phase space is 5.7. In order to test the effect of the forecast model, with the aid of the MATLAB simulation experiments, he traffic flow data by a group of 10 min, call 291 records, first extracted 200 records for training, the remaining 91 records for the validation of the prediction results.

The predicted values of the traffic flow in the same time period are obtained from the trained ANFIS network model (Table 1).

Analysis of training results and measured values (Table 2).

Table 1 Traffic flow forecast value for every 10 min

Time period	9:00–9:10	9:10–9:20	9:20–9:30	9:30–9:40	9:40–9:50	9:50–10:00
Traffic flow	181	164	182	142	170	158

Table 2 The results of traffic flow forecast

Time period	Actual flow	Predicted flow	Prediction error %
1	181	196	−8.2
2	164	150	8.5
3	182	176	3.2
4	142	149	−4.9
5	170	161	5.2
6	158	152	3.7

4 Conclusions

Wavelet analysis has the characteristics of effective analysis in the numerical value. At the same time, ANFIS has strong information storage and learning ability, especially the ability to use knowledge to deal with fuzzy situation. In this paper, wavelet analysis and ANFIS are combined to analyze the traffic time series of a certain intersection. The adaptive fuzzy neural network model (ANFIS) is used to simulate the experiment. The experiment results show that the method is used to predict the traffic flow in a certain period of time.

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