Prediction of Traffic Flow on Highway Ramp in Scenic Area

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Abstract. Through the phase space reconstruction technology, it is proved that there are chaotic behaviors on highway ramp. The establishment of a traffic flow prediction model can also solve the impact of unexpected accidents or delayed management. Short term traffic flow prediction is also an important prerequisite for the intelligent traffic management system. The wavelet transforms neural network can be used to realize the short-term prediction of the traffic flow on the highway ramp.

1. Introduction

In recent years, tourists in Huangguoshu scenic area have seen a ‘blowout’ growth, and the number of self-driving tour vehicles has increased. The traffic volume of highways, especially the section from Longgong to Huangguoshu of Shanghai Kunming expressway has increased sharply. Long distance traffic congestion on Huangguoshu ramp from Anshun to Kunming is slow, and large-scale congestion sometimes occurs. It brings great pressure and accident hidden danger to highway traffic safety supervision, and affects tourists' good travel experience. In order to solve the congestion problem of Huangguoshu interchange exit, it is necessary to carry out a chaotic prediction of traffic flow on the off-ramp of Huangguoshu scenic spot. The research of traffic flow is an important topic in scenic spot management, which involves the analysis of traffic flow distribution and the prediction of traffic flow. The temporal and spatial distribution trend of traffic flow plays an important role in scenic spot management and resource scheduling. The results of traffic flow analysis and prediction are the basis and basis for scenic spot managers to make decisions and provide tourism services.

Short term traffic flow prediction, as a research hotspot of the intelligent transportation system (ITS) at domestic and abroad, has achieved fruitful results in different development periods[1]. The research trend is mainly from a single parameter statistical model to a non-parameter model and a combination forecasting model. The mountain expressway system is a highly unstable and non-linear complex system. Factors such as weather changes, road failures, and holidays have a great influence on the traffic state of the originally closed expressway system. Qiangqiang Zhang designed a BP neural network to predict traffic flow during a peak period in a section of Beijing[2].

The wavelet neural network (WNN)[3, 4] model is formed by combining the traditional wavelet analysis theory with the artificial neural network theory. The biggest advantage of this network is that the processed signal has good local performance and high fault tolerance in both the time domain and frequency domain. The related research shows that WNN can be divided into two types according to the different combination methods: loose wavelet neural network and fusion wavelet neural network. The wavelet neural network, which combines wavelet theory and artificial neural network theory. The fusion WNN is a widely used structure in the current research, and it is also the network structure used...
in this work. The basic idea of the fusion wavelet neural network was proposed by Zhang Qinghua et al. in 1992. The construction idea of the network is to replace the neurons in the traditional neural network with wavelet elements (wavelet function instead of Sigmoid function). The connection between wavelet transform and network coefficients is established through affine transformation, which has better performance than traditional neural networks.

2. Chaos Identification Method of Traffic Flow

In chaos theory, numerical methods are often used for the identification of chaos. There are phase trajectory diagram method, Poincaré map method, power spectral density method, Largest Lyapunov exponent (LLE), Kolmogorov entropy analysis, and correlation dimension method. The highway ramp system has the characteristics of high uncertainty, nonlinearity, complexity, and hugeness. Since chaos theory was introduced into the traffic field, many people have analyzed, predicted, judged, and studied the chaotic phenomena and characteristics in the traffic.

2.1. Phase Space Reconstruction

It is proved that there are three states of traffic flow: free-flow state, synchronous flow state, and blocked flow state. It is also proved that chaos and fractal phenomena exist widely in the state of traffic jams. However, it is impossible to establish an analytical dynamic model for such a complex uncertain system. According to the collected limited time-series data, the phase space reconstruction technique is used to reconstruct the attractor to study the dynamic behavior of the system[5]. That is, according to this ‘one-dimensional’ time series to restore and describe the original complex nonlinear dynamic behavior, so as to determine whether the nonlinear system is in a chaotic state.

In order to extract more useful information from the time series, in 1980, Packard et al. proposed two methods for time series reconstruction of phase space: derivative reconstruction and coordinate delay reconstruction. The essence of the coordinate delay reconstruction method is to construct a D-dimensional phase space vector through the different delay times τ of the one-dimensional time series \( \{ X(i) \} \). In 1981, Takens proposed the embedding theorem: for an infinitely long, noise-free one-dimensional scalar time series of \( m \)-dimensional chaotic attractors, a one-dimensional embedding phase space can be found under the condition of topology invariance, as long as the dimension satisfies \( m \geq 2D+1 \), D is correlation dimension. The calculation principle of the embedding dimension is to ensure that the dynamic behavior of the motive power system can be fully described. Here, the C-C method proposed by Kim et al. is used to determine the embedding dimension, and the delay time \( \tau \) is calculated using the most common self-correlation method.

2.2. Lyapunov Exponents

The Lyapunov exponents (LEs) are an important quantitative index to measure the dynamic characteristics of the system. It represents the average exponential rate of convergence or divergence between adjacent orbits in phase space. For the existence of dynamic chaos in the system, we can judge whether the LLE is greater than zero or not. A positive LEs means that in the phase space of the system, no matter how small the distance between the initial two trajectories is, the difference will increase exponentially with time, so that it can not be predicted. This is chaos.

3. Chaos in Highway Ramp

3.1. The Improved LEs Method

The LLE is the most common parameter to test whether the system has chaotic behavior. In Wolf algorithm, to calculate the LLE, it needs a large number of data points. Generally, the sample size of the time series is greater than 1500. If there are less than 1500 samples, it cannot be used to judge whether there is chaos, but so many samples are difficult to meet the needs of real-time control of the road traffic system. Due to the high real-time requirements of traffic control, we need to quickly and accurately calculate the LLE of the system with a small sample series. Here, an improved maximum Lyapunov exponent method is used to quickly calculate the LLE of the system.
In this work, an improved Lyapunov method with small data volume is used to improve the efficiency of the algorithm. The specific implementation process is shown in Figure 1.

3.2. Chaos in the Ramp
In order to verify the existence of chaos in the highway ramp, we are now experimenting with data from the Open Data Retrieval Platform. The data is at the entrance of a high-speed ramp at a water park during the holiday rush hour on April 11, 2016. The detector collects the average speed every 5 minutes, a total of 500-time series, and analyzes the chaotic characteristics of the highway speed.

According to the calculation steps of the improved LLE method shown in Figure 1, we obtained the LLE is from small data. The curve graph of $y(i) - i$ and its slope change diagram are shown in Figure 2, in which the slope of the curve in the initial test stage is 0.4003. That is, the LLE of the system is 0.4003. Therefore, it can be determined that there are chaotic characteristics of the traffic sequence in the freeway ramp.

4. Short-term Prediction of Highway Ramp Traffic
Due to its strong adaptability, fault tolerance, and learning ability, as well as its unique advantages in dealing with nonlinear problems, artificial neural networks (ANN) are widely used in various fields. The Fourier transform describes a signal in the time domain as the sum of several precise frequency components. After a signal is converted from the time domain to the frequency domain, information about the time of the signal is often lost. The wavelet analysis theory is expressed as the sum of the time domain components describing the sub-bands. So the system can be studied under multiple time scales, which is often regarded as a breakthrough development.
4.1. Wavelet Analysis

Wavelet analysis was developed to solve the deficiencies of the Fourier transform. Wavelet transform is divided into three categories: continuous wavelet transform, discrete wavelet transform, and wavelet transform based on multi-resolution. The expression of the continuous wavelet transform is shown in Equation (1).

\[ f_x(a,b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{a}} \phi\left(\frac{t-b}{a}\right) dt, a > 0 \]  

(1)

where, the parameter \( a \) is the scale factor, when \( |a| > 1 \), the wavelet is an expansion of the original wavelet. when \( 0 < |a| < 1 \), a wavelet is a form of compression. The parameter \( b \) is the translation factor, which determines the time position of the wavelet transform. The analysis of all wavelet coefficients requires too much to compute. A discrete subset is often selected from all the parameters to reconstruct a signal with wavelet coefficients. In this case, all discrete subset points \( (a_n, b = na_n) \) \((m,n \in Z)\) can be selected.

Discrete wavelet transform (DWT) adopts multi-resolution pyramid decomposition technology. The researchers used a high pass filter and a low-pass filter to divide the digital time signal \( S(n) \) into two parts: detailed signal \( X_{1}(n) \) and smooth signal \( W_{1}(n) \). In order to further improve the frequency resolution and approximate coefficients of the decomposed high pass and low-pass filters, this decomposition is repeated many times so that a detailed set of signals \( (X_1(n), X_2(n), \ldots) \) and \( (W_1(n), W_2(n), \ldots) \) can be obtained. DWT is easy to operate and reduces the computation time and resources. In our discrete subset, the scaling parameter \( a \) is equal to \( 2^n \), and the translation parameter \( b \) is equal to \( 2^n \) \((m,n \in Z)\). The discrete wavelet transform can be obtained by replacing the parameters in Equation (1).

4.2. Wavelet Neural Network

The output value predicted by the artificial neural network is Equation (2).

\[ y_i = W(y_{i-1}, y_{i-2}, \ldots, y_{i-p}, \omega) \]  

(2)

where \( \omega \) is a vector parameter and a function determined by the network structure and the parameters. The output expression of the hidden layer is Equation (3).

\[ y_i = \alpha_0 + \sum_{j=1}^{g} \alpha_j g\left(\beta_{0,j} + \sum_{i=0}^{p} \beta_{i,j} y_{i-i}\right) + \epsilon_i \]  

(3)
where \( \alpha_j (j = 0, 1, \ldots, q) \) and \( \beta_i (i = 0, 1, \ldots, p; j = 0, 1, \ldots, q) \) are network connection weights, \( p \) is the number of input nodes, and \( q \) is the number of hidden nodes, \( g(x) \) is the transfer function of the hidden layer. Combined with the discrete wavelet transform, the predicted value can be obtained from Equation (2) according to the past observations. In Equation (2), if \( p \) is large enough, there is a good prediction result, and it can predict any function. In the process of prediction, mean square error (MSE) is used to estimate the overall accuracy, and the absolute percentage error (APE) is used to measure the accuracy index. The expressions of APE and MSE are listed as Equations (4) and (5), where \( y_i \) represents the original value of the i-th traffic flow, and \( \hat{y}_i \) represents the predicted value of the i-th traffic flow.

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2
\]

(4)

\[
APE = \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\%
\]

(5)

4.3. Traffic Flow Forecast Results

The time span of short-term traffic flow forecasting generally does not exceed 15 minutes. The data in Section 3.2 is still used as the learning sample, the sequence number is 500, and 120 samples are selected for testing.

The MSE value in Figure 3 shows that when the number of iterations reaches 450, the decreasing speed of the neural network error value has changed very little. This shows that after 450 iterations of training, the error of the neural network has converged to an optimal value. And its correction of network weights and wavelet function parameters has been relatively small. Figure 4 shows the specific predictions and real data comparisons for each sample. Figure 5 is the APE of short-term traffic flow prediction using a wavelet neural network.

![Figure 3](image)

**Figure 3.** The relationship between the training iterations and MSE

5. Conclusions

Combining traditional wavelet analysis theory with artificial neural network theory, a WNN model is formed. Through the phase space reconstruction technology to analyze the traffic flow in the scenic highway ramp, it is found that there are chaos behaviors. Using WNN prediction, real-time prediction data is obtained, and a lower prediction error rate is given.
Figure 4. Comparison of traffic flow prediction and real value

Figure 5. The absolute error of prediction

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