Short term traffic flow prediction based on multiple time series data and improved Elman neural network

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Abstract. To improve the short term traffic prediction precision, this paper proposes an improved Elman neural network (ELMNN) model for the prediction work. The model input includes two parts: the measured flow data and the theoretical flow data obtained by traffic occupancy and speed. Furthermore, in order to capture the inner regularity of the time series data, the theoretical flow data and the measured flow data are both reconstructed using a phase space reconstruction method. Finally, the reconstructed data are put into the improved ELMNN model, which is developed by employing the mind evolution algorithm (MEA). Compared with the original models, the results of the case study show that the proposed model can obviously improve the prediction accuracy.

1. Introduction

With the rapid development of traffic big data and intelligent traffic system, the drivers are able to get more accurate and timely traffic information, of which the most fundamental is the traffic flow information of the road network. Therefore, accurate traffic flow prediction is of vital importance and many researchers worldwide have concentrated on the study of effective traffic prediction model which features for merits in different aspects. This paper proposes a combined traffic flow prediction model based on the chaos theory and the Elman neural network improved by the mind evolution algorithm. In the chaos theory literature, Takens[1] proposed a method of phase-space reconstruction to process time series data and Zong Chunguang et al. [2] introduced the analysis method of chaos theory into short-term traffic flow prediction. Jiang Xiao [3] studied the phase space reconstruction of multi-parameter time series, conducting the short-term traffic flow prediction research of multi-source data fusion. In the neural network model literature, Navneet et al.[4] compared several neural networks and showed that the ELMNN is more accurate than other neural network structures and conventional methods, and many algorithms have been used to optimize the weights and thresholds of neural network[5].The current studies have proved the lift in prediction accuracy but there are still some drawbacks such as easily trapped in local optimal solution and premature.

In order to solve these problems, this paper proposes an Elman neural network optimized by Mind evolutionary Algorithm (MEA). MEA has stronger global searching ability and can overcome the GA’s defect of premature. In this paper, a traffic flow prediction model based on phase space reconstruction and the MEA improved ELMNN is established, with the observed traffic data, the model is proved more advanced in accuracy and efficiency.
2. Methodology

2.1 Phase space reconstruction
The phase space reconstruction theory is first put forward by Packard and Takens and is used in nonlinear time series analysis. The theory indicates that all the dynamic information of a system can be shown by one of its variates, whereby the reconstructed time series retains the most important characteristics of the original time series.

Set a discrete chaotic time series as \( x_i = \{x_1, x_2, ..., x_N\} \), where \( N \) is the length of the series, then the reconstructed phase space can be listed as:

\[
X_i = x_i, x_{i+\tau}, ..., x_{i+(m-1)\tau}, i = 1, 2, ..., N - (m - 1)\tau
\]

(1)

Where \( m \) represents the embedded dimension and \( \tau \) represents the embedded delay, while \( X_i \) is the phase point of the phase space.

The reconstructed system is topological equivalent to the original system and the state of the next moment can be obtained from the current state of the system, so as to obtain the predicted value of the time series.

The key step of phase space reconstruction is the determination of \( m \) and \( \tau \), currently the commonly used methods to determine \( \tau \) are autocorrelation method, cross correlation method and the mutual information method as well. While the C-C method, the false nearest neighbors method are often used to determine \( m \). After referring to relevant literatures, this paper uses the mutual information method and the false nearest neighbors method to determine \( \tau \) and \( m \) respectively.

2.2 proposed algorithm model
The proposed model is an Elman neural network improved by mind evolution algorithm, which can overcome the defects of the simplex Elman neural network so as to lift the accuracy.

MEA algorithm is firstly put forward by Sun Chengyi in 2000, which is a simulation of the human mind evolution progress and the key steps are "convergence" and "dissimilation". Convergence is the process to learn from the prior individuals constantly while dissimilation is the process for the prior individuals to get into a more superior group. In the process of repeated "convergence" and "dissimilation ", the global optimal solution is obtained.

Elman neural network is firstly put forward by Elman in 1990, with an additional adapting layer in the hidden layer of the feedforward network, the ELMNN has the ability of short time memory and can resist the peripheral noise and approximate any continuous function accurately.

As the chaotic system is sensitive to noise and a tiny change to the initial value can influence the whole system, the ELMNN with robustness is fitter for chaotic time series prediction compared with other models. The nonlinear state space equations of the ELMNN are shown as follows.

\[
y(k) = g(v^T x(k) + b_2)
\]

(2)

\[
x(k) = f(u^T x_c(k) + w^T u(k-1)) + b_1
\]

(3)

\[
x_c(k) = x(k-1)
\]

(4)

Where \( k \) represents the time of the current state and \( y, x, u, x_c \) represent the node vector of \( m \) dimensional output layer, the unit vector of \( n \) dimensional middle layers, the time series traffic flow after construction and the \( n \) dimensional feedback state vector respectively. \( w, u \) and \( v \) represent the weight matrixes that connect the input layer to the hidden layer, the receiving layer to the hidden layer, and the hidden layer to the output layer respectively.

The MEA-ELMNN structure is shown as Figure 1. The input dataset are the phase space reconstructed data of both measured data and theoretical data, the optimal weight and threshold are selected by the MEA with repetitive convergence and dissimilation, afterwards the prediction is carried out using the improved ELMNN.
3. Case study

3.1 Data analysis

The proposed model is applied to the dataset collected from the Remote Traffic Microwave Sensor (RTMS) to testify the accuracy. The RTMS is a traffic sensor which can detect vehicles with microwave signals, the traffic flow, speed and occupancy of each lane are measured every 2 minutes. In this case study, the 900 data groups are collected in the period of 7 to 9 in the morning from April 8 to April 26, 2014, including three factors (average traffic flow \( q_1, q_2, ..., q_n \), average speed \( v_1, v_2, ..., v_n \), average occupancy \( o_1, o_2, ..., o_n \)).

The basic relation of traffic flow between the three basic parameters of traffic flow is:

\[
q = \frac{\bar{v}}{k} \quad (5)
\]

Where \( \bar{v} \) is the average velocity of all the lanes and \( q \) is the total flow while \( k \) is the density.

According to literature \( [6] \), we get to know that the relationship between density and occupation is:

\[
o = (l+d)k \quad (6)
\]

where \( l \) is the length of the vehicle while \( d \) is the detection range, \( l+d \) is a constant, therefore, a theoretical flow \( q' \) is:

\[
q' = \frac{o}{l+d} \bar{v} \quad (7)
\]

The comparison between theoretical flow and measured flow in constantly 4 weekdays can be seen in Figure 2, where they share the same trend, showing that the theoretical flow can express the characters of the measured traffic flow.

Figure 2. The comparison of the measured and theoretical data
3.2 phase space reconstruction
Based on the information theory, the mutual information function of time series is calculated. According to the mutual information method, the first minimum of the function corresponds to the delay time of the time series. False nearest neighbors method features a decreasing false near neighbors rate with the embedding dimension increase, when the false near neighbors rate is to or almost to zero and no longer decrease with the increase of the embedding dimension, $m$ at this point is considered to be the best embedding dimension. In Figure 3, (a) and (b) illustrate that the time delay $\tau$ of measured and theoretical time series are 1 and 2 while (c) and (d) illustrate that the embedding dimension $m$ of measured and theoretical time series are both 4. Afterwards, the measured and theoretical time series data are reconstructed using phase space reconstruction method.

![Figure 3. The determination of time delay and embedding dimension](image)

3.3 prediction of multiple time series data
Based on the phase space reconstructed time series, the prediction is carried out using the MEA-ELMNN model shown in Figure 1, the input layer is determined by the embedding dimensions of two time series data and the output is the prediction result. In Figure 4, (a) is the result of ELMNN with single time series data, (b) is the result of ELMNN with multiple time series data and (c) is result of MEA-ELMNN with multiple time series data.
Figure 4. The prediction result

Table 1. The prediction performance evaluation

| Model                | Mean Average Error (MAE) | Root Mean Square Error (RMSE) | Mean Average Percentage Error (MAPE) |
|----------------------|--------------------------|-------------------------------|-------------------------------------|
| SPSR$^a$-ELMNN       | 10.34                    | 13.07                         | 1.29%                               |
| MPSR$^a$-ELMNN       | 6.14                     | 7.81                          | 1.12%                               |
| MPSR-MEAELMNN        | 3.85                     | 5.07                          | 1.08%                               |

$^a$Phase space reconstruction with single time series data (measured traffic flow data only)

$^b$Phase space reconstruction with multiple time series data (measured and theoretical traffic flow data)

As is shown in Figure 4, the predicted curve in three subfigures all share the same trend with the measured curve, and according to Table 1, the three evaluation indexes of error are all in a low level, proving the ELMNN is a robust model to predict chaotic time series. In Figure 4, the fitting degree of the three subfigures tend to be lifted and in Table 1, the three error indexes involving mean average error, root mean square error and mean average percentage error decrease obviously with the improvement of the model, proving the two proposed methods, multiple phase space reconstruction and mind evolution algorithm, are effective.

4. Conclusion
(1) This paper proposes a method to involve the multiple time series data into the prediction, the multiple time series data is the combination of measured and theoretical data, it contains not only the traffic flow
information but also density and volume. The result of the case study illustrates that it can improve the prediction accuracy.

(2) The mind evolution algorithm, which is advanced than the usually used genetic algorithm in searching the global optimum, has been proven to be effective in improving the ELMNN since the improved model can fit the measured data better.

(3) The proposed multiple phase space reconstruction can not only be combined with the ELMNN but also other algorithms including nonlinear method and other neural network methods, showing that it has advanced performance portability.

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