Short-term Traffic flow Prediction based on Deep Circulation Neural Network

RuRu Liu¹, Feng Hong²*, Changhua Lu³, WeiWei Jiang⁴
¹College of Electrical and Mechanical Engineering, Chizhou University, Chizhou, China
²College of Electrical and Mechanical Engineering Chizhou University Chizhou, China
³College of computer and Information Hefei University of Technology HeFei, China
⁴College of computer and Information Hefei University of Technology HeFei, China

*Corresponding author e-mail: hfeng255@sina.cn

Abstract. The difficulty of traffic flow prediction in intelligent transportation system is its non-linearity and correlation. There are many factors affecting the short-term traffic flow, but the prediction of the traffic flow at the next moment is closely related to the information of the historical moment. In this paper, a prediction model based on deep cyclic network (RNN) is proposed. The feature data are extracted from the data of the relevant time as the reference standard to predict the traffic at the future time. The simulation results show that the prediction effect of this algorithm is obviously improved.

1. Introduction

The ARIMA model for short-term traffic flow forecasting was proposed in 1979 [1], a traffic flow velocity prediction model based on single hidden layer convolution neural network and error feedback is proposed [2]. The real-time adaptive prediction of short-term traffic flow was carried out by using ARIMA model [3]. The ARIMA model was used to forecast the traffic flow on the urban main roads [4]. An adaptive Kalman filter model is proposed for traffic flow prediction [5]. Because of the non-linear and randomness of traffic flow, in order to better capture the characteristics of traffic flow data and the dependence of data, researchers began to try to apply other models in the field of traffic flow prediction. On the basis of comparing the performance of seasonal auto regressive model, Bayesian model and neural network model in traffic congestion and normal state, a traffic flow velocity forecasting hybrid model based on traffic state is proposed in literature [6], support vector machine was used to predict short-term traffic flow and obtained better prediction accuracy [7]. Traffic flow itself is a complex process. The above methods are based on a certain priori knowledge for the feature selection of the sample data, and cannot fully mine the essential features of the data. Short-term Traffic flow Prediction based on Deep Learning, References [6-9] mainly consider the big data characteristics of neural networks, and seldom consider the characteristics of short-term traffic flow. According to the direct correlation of short time traffic flow, this paper presents a kind of short time traffic flow based on deep cycle neural network.
2. Model Design

A. RNN Network Structure

The remarkable feature of a cyclic neural network is that it retains historical data, and the state of the forward moment can be passed to the next, as shown in Fig.1. Based on the hidden state $h_{t-1}$ of the previous moment and the input $x_t$ of the current moment, the hidden state $h_t$ of the current moment can be calculated. The network can process any length of time series, and the prediction time of traffic flow is a relatively long continuous period. Simultaneous cyclic network prediction of the current time series, it is calculated that the state of the previous moment and the state of the current input are predicted together, so that the prediction can be carried out by pushing back to the initial value continuously, and the results are timely and accurate.

![Fig.1. Schematic structure of RNN](image)

In the figure above, you can write out the relationship between the state value and the weight such as:

$$h_t = \tanh(\omega_{sh} \cdot x_t + \omega_{hh} \cdot h_{t-1} + b)$$

$$h_t = \omega_{hh} \cdot h_{t-1},$$

the changes are as follows:

$$h_t = (\omega_{hh})^t \cdot h_0,$$

For $\omega_{hh}$ diagonal transformation:

$$h_t = (\omega_{hh})^t \cdot h_0 = \vartheta \cdot \Lambda \cdot \vartheta \cdot h_0,$$

the disadvantage of single cyclic network is that it can easily cause gradient to disappear or explode in the process of training. When the eigen-value is > 1, it tends to be infinite, the loop network can easily lead to a gradient explosion; the eigenvalue is < 1, it tends to be infinitesimal or zero, circular networks can easily cause gradient to disappear. In this paper, in order to prevent the gradient from disappearing or exploding, we choose the network that combines the cyclic network and the short-term memory network in order to prevent the gradient from disappearing or exploding.

B. LSTM Network Structure

Long-term and short-term memory networks are characterized by three control gates to control which portions of information are retained, added, and which information is used as output. The principle of long-and short-term memory networks is shown in Fig.2. The core structure of the network is the belt structure plus control gate. The three doors are: forgotten door, input gate and output gate.

![Fig.2. Schematic diagram of long-and short-term memory network](image)

Fund projects: An Hui Province University excellent Young Talent Project (gxyq2018110)
Correspondence author (*): Feng Hong email: hfeng255@sina.cn
The expression for the forgotten door is: 
\[ f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \]  
(1)

The expression of the input door is: 
\[ i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \]
\[ \tilde{C} = \tanh(W \cdot [h_{t-1}, x_t] + b_c) \]
(2)

The purpose of the input gate is to decide how much information to add, \( \tanh \) generates alternative content vectors to update; The sigmoid layer determines which information needs to be updated.

Output gate expression:
\[ o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \]
\[ h_t = o_t * \tanh(C_t) \]
(3)

The output gate determines the state output value \( \tanh \) normalizes the information to \([ -1, 1] \), The sigmoid layer determines which information is output.

C. Model Construction

Based on the characteristics of cyclic network and lsmt network, the network structure of this paper combines the two, The designed network mainly combines the two to predict the traffic flow based on short time, because a single circular network can cause gradient to disappear or gradient to explode, RNN that causes network standards to be easily passed away. The LSTM and the cyclic network are combined to make the eigenvalue equal to one to avoid the gradient

Fig3. RNN- LSTM schematic diagram of network structure

3. Simulation Result

By sampling data at a certain intersection, the time of sampling data is a sample of intersection flow for a month in a row. Using the network model structure proposed in this paper, after the training is completed, the short-term traffic flow can be predicted. Through model training to temporarily do not consider the weather, holidays and other special reasons caused by unusual conditions, mainly considering the normal period of time from normal Monday to Friday, a section of traffic flow information, to predict the short-term traffic flow on this section of the road. The following figure is displayed by simulation.

Fig. 4. Schematic diagram of simulation results
4. Conclusion

In this paper, the network structure is mainly based on the combination of cyclic neural network (RNN) and memory network (LSTM) based on long and short term. It can avoid the shortcoming of single cycle neural network, and make use of the network structure combining long and short term memory network to improve the result of training, which is closer to the real value, and achieves the expected effect effectively. However, there are still some problems, such as data collection, factors affecting data collection, etc. which have not been taken into account for the time being.

References

[1] HUANG W, SONG G, HONG H, et al. Deep architecture for traffic flow prediction: Deep belief networks with multitask learning[J]. IEEE Transactions on Intelligent Transportation Systems, 2014, 15(5):2191-2201.

[2] Liang Ke, Tan Jianjun, Li Yingyuan. A short time Traffic flow Prediction method based on mapreduce[J], computer project, 2015, 41(1):174-179.

[3] LV Y, DUAN Y, KANG W, et al. Traffic flow prediction with big data: A deep learning approach[J]. IEEE Transactions on Intelligent Transportation Systems, 2015, 16(2): 865-873.

[4] Kang Jun, Duan Zongtao, Tang Lei, et al. Gauss process regression Short-time Traffic flow Prediction method[J]. Transportation system Engineering and Information, 2015, 15(4): 51-56.

[5] YANG H F, DILLON T S, CHEN Y P. Optimized structure of the traffic flow forecasting model with a deep learning approach[J]. IEEE Transactions on Neural Networks & Learning Systems, in press, doi:10.1109/TNNLS.2016.2574840.

[6] Zhou Tong, Yang Zhiyong, Sun Dihua, et al. Study on Short-term Traffic flow Prediction method of Freeway based on vehicle Type[J]. Computer application research, 2015, 32(7): 1996-1999.

[7] Tan Guoping, Liu Rutong, Tan Lin Fung. Research on congestion Detection Mechanism based on vehicle Cooperation[J]. Electronic Design Engineering, 2016, 24(21):118-121.

[8] Zhang Hongbin, Sun Xiaoduan, He yulong. Analysis and Prediction of complex dynamic characteristics of Short-Time Traffic flow[J]. journal of physics, 2014, 63(4): 51-58.

[9] Yang Chunxia, Fu Yiqin, Bao Tienan, et al. Short-term Traffic flow Prediction based on similarity[J]. Highway traffic technology, 2015, 32(10):124-128.