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Navigation Density Prediction of ConvLSTM Model based on Multi-features

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Abstract

The waterborne traffic density in the field of intelligent transportation is nonlinear, unstable and fluctuating, etc. So the accurate prediction of traffic density is faced with challenges. In addition, waterway transportation is an important way of logistics and trade in China. Compared with road transportation, waterway transportation has higher safety and lower cost, so it is particularly important for us to predict the accuracy of waterway traffic density. In this paper, a multi-feature graph convolution and long and short time memory network model is proposed to solve the spatio-temporal correlation problem of traffic flow data and realize the prediction of traffic density in water transportation. The model uses graph convolution operation to extract spatial features and short and long time memory network to extract temporal features. Three related features of ship's navigable density, ship's average speed and ship's density are introduced to achieve more accurate traffic volume prediction. Experimental verification of the model was carried out on the real AIS data set. Through multiple groups of comparative experiments, the experimental results showed that the proposed model was better than the baseline LSTM network and the single-feature graph convolution LSTM model in predicting the navigable density of water transportation, with the accuracy increased by 25% and 13% respectively.

Keywords

Waterborne Traffic Density; Figure Convolution; LSTM; Spatio-temporal Correlation; Multi-feature.

1. Introduction

Compared with land transport, waterway transport is safer and cheaper, so waterway transport has been an important way of logistics and trade in China since ancient times. On the one hand, China's inland river shipping has promoted the development of Chinese economy and society and improved the living standards of the people along the waterway. On the other hand, because the increase of inland shipping vessels makes the waterway crowded, the backward supervision equipment of inland waterway leads to frequent traffic accidents and a large amount of economic losses. In order to improve the supervision level of inland river shipping in our country and reasonably plan inland river shipping traffic, it is necessary to establish a perfect inland river shipping supervision system.

With the increasing of China's economy, it provides new opportunities for the development of inland water transportation in China. Inland water transportation plays a very important role in Chinese comprehensive transportation, but there are still many problems which are the influence and restriction of many unfavorable factors in the development of China's inland water transportation. Firstly, we analyzed the present situation of inland water transportation development. Secondly, in view of these adverse factors, we put forward targeted measures to promote the coordinated

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development of inland water transportation and related departments, safeguard the legitimate rights of water transportation and give play to its important role in China's transportation.

Chinese inland waterway transportation is dominated by the Yangtze River and the Beijing-Hangzhou Canal. The inland waterway ships are dominated by cargo ships, whose track has strong regularity. Navigable density refers to the number of ships or fleets passing through a section of a waterway in a unit time. It is an important volume of traffic to evaluate the navigability of ports and waterways in waterway transportation. Traffic density prediction can provide reliable data supporting for the construction of inland wharf and waterway, ship navigation safety warning and wharf site selection, etc. So it has important practical significance for the construction of smart water transportation. Navigation density is a typical spatio-temporal data which shows correlation and heterogeneity in both time dimension and space dimension. Therefore, traffic density prediction is one of the research hot topics and difficulties in smart water transportation.

Traffic volume prediction is a typical spatio-temporal data prediction problem. Different types of traffic data are embedded in continuous space and change dynamically with time.In particular, scholars apply the deep learning method to the prediction of spatial-temporal data. Convolutional Neural Network (CNN) can effectively extract the spatial features of grid data and well extract the spatial features of traffic volume. Although the problem of traffic volume prediction has achieved great results in the field of road traffic, the method of data collection and domain characteristics of water traffic are different from that of road traffic or urban traffic. Therefore, the existing traffic volume prediction methods in road traffic are not applicable to the spatial characteristics of waterway network and can't solve its spatio-temporal correlation analysis problems.

Ship traffic flow prediction is a new subject emerging in recent years, which combines the theory of traffic engineering with the theory of economic prediction and can predict the overall ship traffic flow in a certain channel in the future. Ship traffic flow prediction has important applications in many aspects, including channel planning, site selection of monitoring base station, ship traffic management and so on. In this paper, we study the method of ship traffic flow prediction in inland waterway and conclude an optimized ship traffic flow prediction technology in inland waterway based on neural network algorithm.

For Marine traffic density prediction problem, this paper proposes a traffic density prediction method based on the deep learning which names multiple features convolution LSTM (MFConv - LSTM) model. It starts from the multiple traffic associated with water transportation traffic density, using convolution neural network network together with both short-term and long-term memory, in to join the multiple features of the fusion, which effectively captures the spatio-temporal correlation data. The main contributions of this paper are as follows:

i) Based on the reality of inland river transportation, this paper analyzes multiple features of water transportation and uses effective methods to assign the weight of features.

ii) We propose a new model which names multi-feature ConvLSTM model, which can extract spatial features through convolution and temporal features through LSTM.

iii) Based on the real ship AIS data set (ship position perception), we established the waterway traffic density prediction data set and a variety of algorithm comparative experiments were carried out on it to verify the effectiveness of the prediction method proposed in this paper.

2. Correlational Studies

In fact, the forecast of traffic density can also be summarized into the forecast of traffic flow. In the past few decades, researchers at home and abroad have proposed many kinds of short-term traffic flow prediction models, which can be roughly classified into three categories. The first type is the model based on mathematical statistics, which makes use of the theory and method of mathematical statistics to analyze and predict the traffic flow data. Ahmed first proposed the auto-regressive moving average (ARIMA)[1] model to predict the short-term traffic flow of expressways. Since then,

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researchers have made various improvements of ARIMA to develop more accurate predictive models. Due to the non-linearity and randomness of traffic flow, such methods have high requirements for data and can not deal with nonlinear traffic data and the randomness and complexity of short-term traffic volume prediction. The second category is traditional machine learning methods, which can model more complex data, such as K-nearest neighbor method, support vector machine and so on.This kind of method cannot effectively consider the spatio-temporal correlation of traffic data at the same time and requires a lot of feature engineering. The third category refers to deep learning, which gives full play to the advantages of each prediction model and overcomes their shortcomings, so as to achieve the purpose of improving the prediction accuracy.

In recent years, deep learning has been applied to traffic volume prediction[2], which has become a research hotspot in the field. How to model the complex spatio-temporal dependence is the key point of traffic volume prediction. For this kind of spatio-temporal prediction problem, the research work is mainly carried out from two aspects: one is to regard the spatial dependence as static and then to define the spatial dependence by graph convolution; Second, time dependence is regarded as strictly periodic and dynamic spatial dependence is modeled by graph convolution method.

Long -short -term memory network technology has become a popular time-series modeling framework because of its end-to-end modeling, easy to reflect exogenous variables and automatic feature extraction. Scholar Ma Xiaolei[3] and Wang Yinhai first applied LSTM to the field of traffic and predicted the future road traffic speed with the help of sensor data. Later, scholar Ma Xiaolei[4] proposed a traffic speed prediction method based on convolutional neural network (CNN), learning the traffic network as an image and predicting the traffic speed in a large scale and the scope of the network. From the time characteristics of traffic flow data and periodic characteristics, spatial characteristics, cholar Feng Xinxin[5] combine CNN and LSTM with a Conv - LSTM module, because convolution (Convolutional Neural Networks, CNN) without artificial neural network for preprocessing and spatial distribution of extra complex operations, such as feature extraction, but by its unique fine-grained automatic processing spatial data feature extraction ways. When processing time characteristics, LSTM can effectively avoid the disappearance of effective information caused by long data interval span. If the parallel CNN and LSTM are used to extract the spatial and temporal characteristics of traffic flow respectively, there are some limitations. For example, in the parallel structure composed of CNN and LSTM, the input and output of the two are relatively independent and the extraction of the relationship between different features is ignored.

The prediction[6] of navigable density in waterborne transportation is a core problem in waterborne intelligent transportation. It is different from traffic volume prediction in road traffic, because the volume of traffic collected in road traffic is usually relatively dense and stable, which has obvious periodicity and trend. However, water transportation is limited by collection means and other factors, such like more traffic volume error, longer time interval. Its traffic volume is characterized by non-stationarity and insignificant periodicity[7]. Therefore, it is more difficult and challenging to predict the traffic volume of waterway traffic.

Scholar Ma Xiaolei and Feng Xinxin both use the data of urban traffic flow, so the input is basically the average speed and flow of vehicles in the city. Nevertheless,in water transportation, the data collection is much more difficult than that on the highway. What’s more, the noise of data collected is relatively large and the difficulty of data processing is relatively high. Furthermore, in shipping, the average speed of ships and other data cannot be the same as that of highways, because the average speed of highways[8] is basically limited by the traffic flow. The smaller traffic flow is , the faster average speed is, and vice versa. The difficulty of data analysis is much higher than that of highway, so this paper adopts the multi-feature method, through three features of ship navigation volume, ship average speed and ship density, which is assisted by graph convolution to extract spatial features, short and long time memory network to extract time features and finally form the Conv-LSTM model of graph convolution with multiple features (MFGCONV-LSTM).

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3. The Model

We define water transportation network[9] as undirected graph G = (V, E, A), as shown in figure 1, among them: V for the node set, i.e. port or channel important nodes (such as Bridges, locks, etc.), | V | = N is the number of nodes; E is the set of edges, representing the connectivity between nodes; $A \in R^{N \times N}$ is the adjacency matrix of graph G. Each node on the waterway network G will detect F time series data with the same sampling frequency, that is, each node will generate a feature vector of length F in each time period.

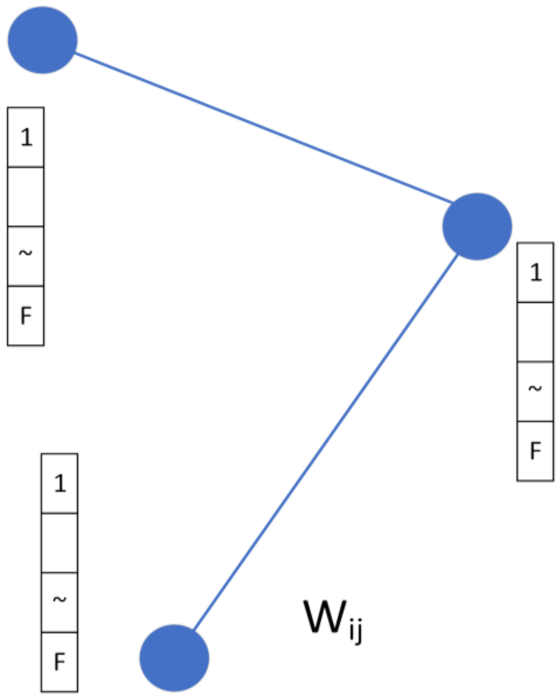

Figure 1. Water transport network

The MFGCONV-LSTM structure is shown in Figure 2.

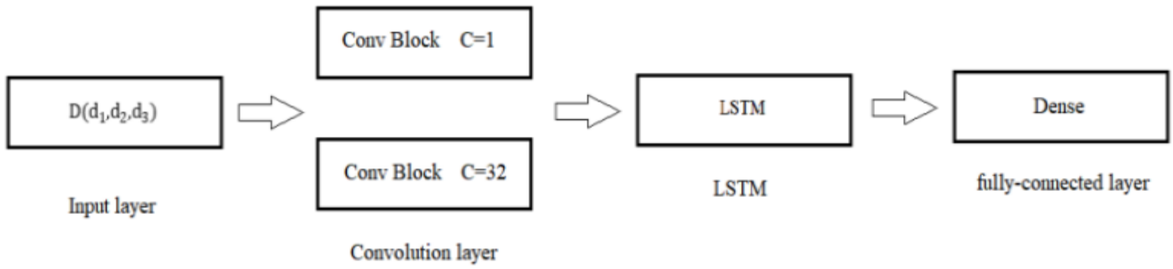

Figure 2. MFGConv-LSTM Model structure

Input layer: sort the data of the three regions in time sequence and calculate the ship's navigation volume, average ship speed and ship density on the ship's AIS data set at the time interval of half an hour. The above three indicators are taken as the features of MFGCONV-LSTM and the data is integrated into the form of a third-order tensor, $D(d_1, d_2, d_3)$, where di is node set, feature vector and time dimension respectively.$D_{ij} \in R^T$ represents the time series of the eigenvalue of node i and the jth term of the feature vector. Let the first time series of each node $f \in (1, \ldots, F)$ be the navigation density series and the navigation density within a certain period of time in the future be the target to be predicted.

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Graphic convolution layer: as the key to extract the spatial correlation of traffic data from the model in this paper. The input of each neuron in the convolutional layer is connected to the previous layer for local feature extraction. In this paper, there are two sequential convolution blocks and the channel number of the two convolution blocks is divided into 1 and 32.

LSTM layer: The most basic LSTM[10] unit is composed of three gates (input, forget, output) and a cell unit. This is also the core part of LSTM. What's more, LSTM variants such as GRU will be three doors into two doors, but we are mainly to introduce LSTM. Gate uses a sigmoid activation function, while input and cell state are usually converted using tanh.

Gates:

$$\mathrm{f_t} = \sigma(\mathrm{W_f} \cdot [\mathrm{h_{t-1}}, \mathrm{x_t}] + \mathrm{b_f}) \tag{1}$$

$$\mathrm{i_t} = \sigma(\mathrm{W_i} \cdot [\mathrm{h_{t-1}}, \mathrm{x_t}] + \mathrm{b_i}) \tag{2}$$

$$\mathrm{o_t} = \sigma(\mathrm{W_o} \cdot [\mathrm{h_{t-1}}, \mathrm{x_t}] + \mathrm{b_o}) \tag{3}$$

The input transform:

$$\tilde{C_t} = relu(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{4}$$

Status updating:

$$\mathrm{C_t} = \mathrm{f_t} * \mathrm{C_{t-1}} + \mathrm{i_t} * \tilde{\mathrm{C}}_\mathrm{t} \tag{5}$$

$$h_t = o_t * relu(C_t) \tag{6}$$

In the MFGCONV-LSTM model, the number of neurons in the LSTM layer is 64 and the activation function selected is ReLU. Because when the value of neurons of ReLU function is greater than zero, the gradient of ReLU is constant as 1. What's more, the gradient can be transmitted all the time when the value is greater than zero. Furthermore, the convergence rate of the SGD obtained by ReLU is much faster than that of tanh.

Output layer: after flattening the data from 2 dimensions to 1, a full connection layer is used to output the predicted value of ship navigability.

4. Experiments

In this section, we mainly introduce the experimental process and the analysis of the experimental results.

4.1 Data preprocessing and data set description

In this paper, we adopt the AIS data of ships in the ports of the lower reaches of the Yangtze River provided by the real Hifleet platform. The dataset includes the pre-designated waters of Taicang Port (31° 31.38'N-31 ° 32.42'N, 121° 21.03'E-121 ° 22.42'E), Jiangyin Port (31° 56.35'N-31 ° 57.00'N, 120° 15.83'E-120 ° 16.70'E) and Nanjing Port (32° 10.55'N-32 ° 10.98'N, 118° 54.90'E-118 ° 55.62'E). Ship AIS data for 7 months from 0:00 on March 1, 2018 to 24:00 on September 30, 2018. AIS data of a ship includes: ship MMSI, collection time, ship position (latitude and longitude), heading, ship speed, ship heading, steering speed, AIS message number, ship type and other information.

First of all, incomplete AIS data and abnormal course AIS data were eliminated by data preprocessing. Secondly, three values including ship navigation volume, average ship speed and ship density were counted as the characteristics of the model in this paper respectively for the above areas and the ship AIS data set at a time interval of half an hour.

Definition of ship traffic: the number of ships passing per unit time (to be repeated).

$$\mathrm{C_0} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{c_i} \tag{7}$$

n is the number of ships to be duplicated.

The average speed of a ship is defined as the average of the sum of the speeds of each ship in unit time.

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$$\bar{\mathrm{v}} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{v_i} \tag{8}$$

v_i is the speed of the i th ship within a certain time interval.

Definition of ship density: refers to the number of ships per unit length of a waterway in a certain period of time (without repetition). The specific calculation formula is as follows:

$$\mathrm{k} = \frac{\mathrm{n}}{\mathrm{l}} \tag{9}$$

n is the number of ships not to be repeated, and l is the length of the channel.

4.2 Experimental environment and evaluation indexes

TensorFlow version 2.3.1, Keras version 2.4.0, Numpy version 1.18.5, Matplotlib version 3.2.2, and Scikit-Learn version 0.23.1 were used in the experiment.

We take the mean square error (MSE) and mean absolute error (MAE) as the evaluation indexes for the model proposed in this paper. The specific calculation formula is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_{true} - y_{pred})^2 \tag{10}$$

$$\mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} |\mathrm{y_{true}} - \mathrm{y_{pred}}| \tag{11}$$

4.3 Graph convolution experiment

Through the comparison of Conv-LSTM and LSTM, we can judge whether the experimental results after adding graph convolution are better than that of a single LSTM.

Table 1. Comparison of LSTM and Conv_LSTM

Model	Nanjing		Jiangyin		Taicang	
	MSE	MAE	MSE	MAE	MSE	MAE
LSTM	9.74	4.33	8.45	3.57	5.22	2.49
Conv_LSTM	4.71	1.45	2.87	1.39	2.66	1.23

The batch_size of both groups is 1, the epochs is 100, and the learning_rate is 0.05. As can be seen from the data in Table 1, since LSTM is only related to time correlation, while Conv-LSTM adds spatial and temporal correlation, both MSE and MAE in various regions are superior to Conv-LSTM. It can be seen that in terms of traffic flow data, the prediction accuracy of extracting only temporal correlation is indeed not as high as that of extracting temporal and spatial correlation.

4.4 Multi-feature experiment

The purpose of this group of experiments is to compare the experimental effect of multi-feature MFGConv-LSTM (in this paper) with that of single-feature Conv-LSTM. The prediction accuracy of the single-feature Conv_LSTM and the MFGConv_LSTM model in this paper is compared by selecting the data of one day to predict the data at the point 30, 60, 90 and 120 minutes later.

Table 2. Conv_LSTM and MFGCONV_LSTM comparison table

Model	30min		60min		90min		120min	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Conv_LSTM	3.13	1.87	4.71	3.19	8.53	6.6	11.03	8.75
MFGConv_LSTM	2.78	1.62	3.57	2.86	6.71	5.86	8.59	7.06

The Bacth_size of both groups of experiments is 10, the epochs is 100, and the learning_rate is 0.05.It can be seen from Table 2, Figure 3 and Figure 4 that with the increase of the prediction time, the prediction error becomes larger and larger.However, after the introduction of multiple features, the overall error is smaller than that of CONV-LSTM, which indicates that the reference of multiple features plays a role in the prediction of water transport traffic flow.

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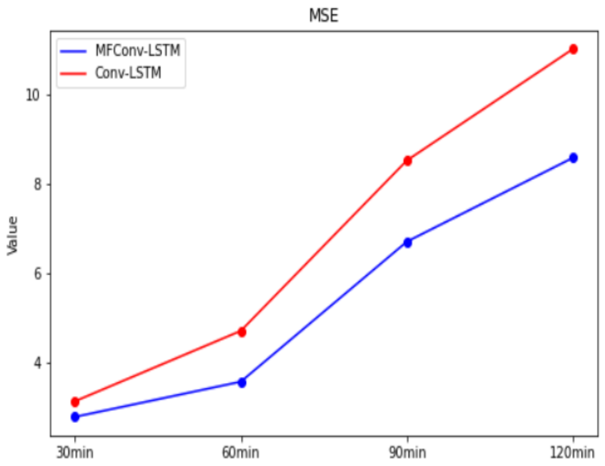

Figure 3. MSE

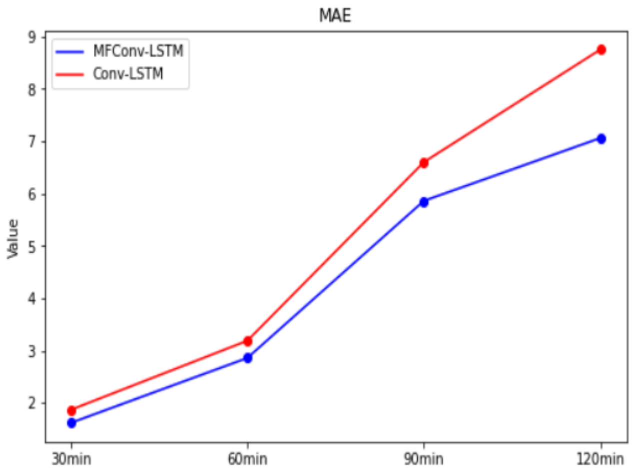

Figure 4. MAE

4.5 Navigation density prediction experiment

In this paper, the MFGConv-LSTM model is used to draw the 6-month prediction of Taicang and compare it with the real value, as shown in Figure 5.

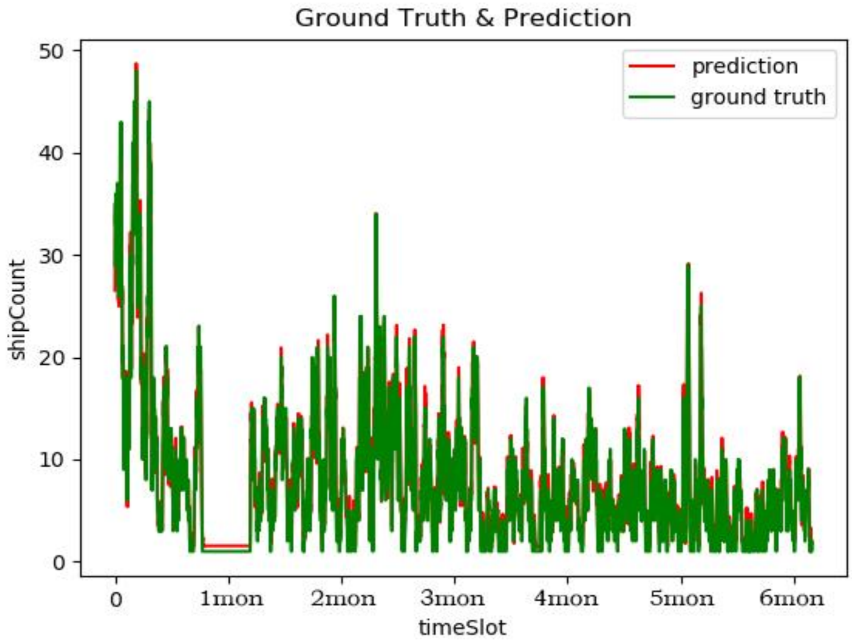

Figure 5. Taicang forecast chart

It is obvious that the graph line of MFGConv-LSTM is very close to the real value, which highlights the superiority of this model in predicting the navigable density of water transportation.

5. Conclusion

In this paper, the way of traditional prediction methods cannot be effectively applied to the navigation of the ship quantity forecast. Through the network diagram convolution, space feature extracting features extracting time length memory network combined two methods. What's more, the average speed, traffic density and vessel density multiple characteristics applied to forecasting model to solve the problem that water transport network traffic is not smooth, strong randomness and no significant cyclical characteristics. The experiment on the AIS data set of inland waterway ships verifies that the

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prediction accuracy of the proposed model is better than that of LSTM and single-feature GCONV_LSTM, which indicates that the MFGCONV-LSTM model has certain advantages in predicting the waterway traffic flow.

References

[1] Williams B M, Hoel L A. Modeling and Forecasting Vehicular Traffic Flow as a Seasonal ARIMA Process: Theoretical Basis and Empirical Results[J]. Journal of Transportation Engineering,2003,129(6):p.664-672.

[2] Guo, Shengnan & Lin, Youfang & Feng, Ning & Song, Chao & Wan, Huaiyu. Attention Based Spatial-Temporal Graph Convolutional Networks for Traffic Flow Forecasting[C]// Proceedings of the AAAI Conference on Artificial Intelligence. AAAI, 2019: 33. 922-929.

[3] Ma X, Tao Z, Wang Y, et al. Long short-term memory neural network for traffic speed prediction using remote microwave sensor data[J]. Transportation Research Part C Emerging Technologies, 2015,54:187-197.

[4] Xiaolei M, Zhuang D, Zhengbing H, et al. Learning Traffic as Images: A Deep Convolutional Neural Network for Large-Scale Transportation Network Speed Prediction[J]. Sensors, 2017, 17(4):818-.

[5] Liu Y, Zheng H, Feng X, et al. Short-term traffic flow prediction with Conv-LSTM[C]//2017 9th International Conference on Wireless Communications and Signal Processing (WCSP). IEEE,2017:23-31.

[6] Man Chuntao, Kang Danqing.LSTM Short Term Traffic Flow Prediction Considering Upstream and Downstream [D], Harbin Institute of Technology, 2019.

[7] Liu Weili.Research on Prediction Method of Ship Traffic Flow in Inland Waterway Based on Neural Network [D]. Zhengzhou City Vocational College, 2018.

[8] Wang Qiuwen, Chen Yanru, Liu Yuanchun.Short Term Passenger Flow Prediction Based on Convolutional Short-Term Memory Neural Network [D]. Southwest Jiaotong University, Jiangxi Normal University, 2020.

[9] Dong Wei, Zhang Leilei, Jin Ziheng, Sun Wei, Gao Junbo. Water Traffic Density Prediction Based on Multi-feature Spatial and Temporal Graph Convolution Network [D], School of Information Engineering, Shanghai Maritime University, 2020.9.

[10] Yan Zhen, Yu Duo, Han Lu, Su Jun, Liu Ping.A Short Term Traffic Flow Prediction Method Based on CNN+LSTM [D].Beijing Technology and Business University, 2019.