Traffic Flow Prediction Based on MLR-LSTM Neural Network

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A prediction method based on the combination of multiple linear regression and Long-Short-Term Memory (MLR-LSTM) is proposed, which uses the incomplete traffic flow data in the past period of time of the target prediction section and the continuous and complete traffic flow data in the past period of time of each adjacent section to jointly predict the traffic flow changes of the target section in a short time.

Keywords: time series ; traffic prediction ; long short-term memory

1. Introduction

In recent years, with the continuous increase of automobile ownership, there are approximately 850 million automobiles in the world. However, the carrying capacity of the road is inconsistent with the growth of car numbers, resulting in long-term congestion and stagnation on the road, which not only reduces traffic efficiency and increases residents' travel time but also increases the risk of traffic crash. In order to ensure the smoothness of the road, it is significant to accurately predict the traffic flow of each section and provide suggestions for traffic diversion. In this research, researchers define traffic flow as the number of vehicles passing in a specified time in the road slice monitored by the camera. Traffic flow data of each adjacent road section should be combined to jointly predict the traffic flow of the target road section allowing partial missing of the past flow data in this research.

Traffic flow prediction is regarded as an important sub-topic in transportation. The prediction methods used in traffic flow have been updated with the development of the times. With the application of big data technology in the field of traffic flow, the neural network method has been widely used in traffic flow prediction. However, this prediction method has strict requirements on data. If the data is partially missing, the effect will be affected. In addition, the traffic flow data changes greatly in the short-term, has many uncertainties, and shows periodicity relative to time. In view of the fact that the current research in this area is not rich enough, the existing methods have a large amount of calculation, high data requirements, and a need for complete and correct data sets, researchers propose a method to obtain accurate prediction when the traffic flow data of the target road section is incomplete. Researchers use the cyclic neural network to predict according to the periodicity of the data, and obtain the prediction value with high accuracy of the target road section through the linear regression of the traffic flow data of multiple road sections.

Today's methods are based on the coordinate data of each road section combined with the graph neural network, and the traffic flow prediction of multiple road sections is obtained after the convolution operation. This method requires a high accuracy of data. If the data is wrong, the whole model result will be inaccurate. The MLR-LSTM proposed by researchers has a high fault tolerance rate. The combination of traditional statistical methods and deep learning makes the model easier to explain and understand.

2. Multi-Section Traffic Flow Prediction Based on MLR-LSTM Neural Network

Analyzing the time series data of traffic flow, mastering the rules, and predicting the flow change in the future for a period of time can provide better traffic control decisions for traffic managers. Therefore, the research on traffic flow prediction has become richer and richer and has kept pace with the times since the last century. Therefore, in addition to the expansion of various branches of traffic flow forecasting, such as single-point forecasting and multi-point forecasting, single-period forecasting and multi-period forecasting, a huge treasure has been formed in the change of forecasting methods. At present, traffic flow prediction methods are mainly divided into model-driven and data-driven methods.

Model-driven traffic flow prediction methods include various prediction models based on nonlinear theory. The nonlinear theories and methods used mainly include catastrophe theory [1], chaos theory [2], wavelet analysis [3], and so on. This kind of model can better fit the characteristics of multimodality, mutation, inaccessibility, divergence, and lag of traffic flow state. Among them, Huang Yanguo et al. [1] (2022) proposed a traffic flow cusp catastrophe model based on traffic wave theory with traffic density as state variables and traffic flow and wave speed as control variables. Anyu Cheng et al. [2] (2017) used the maximum Lyapunov exponent to identify the chaotic characteristics of traffic flow related to speed, occupancy, and flow, and produced a traffic flow prediction algorithm based on multi-source and multi-measure. Yanchi Li et al. [3] (2020) improved a prediction model by combining wavelet analysis and neural networks, which improved the prediction accuracy through the combination of wavelet denoising and BP neural network.

With the rapid development of big data technology, data-driven methods have been widely studied. The early research on traffic flow prediction mainly adopts traditional statistical models, such as the historical average model, time series analysis model, Kalman filter analysis model, support vector regression model, and so on. The typical ha averages the data throughout the period and takes the average value as the prediction value, but this method has low prediction accuracy and the prediction result of traffic flow is not ideal. Time series analysis models mainly include moving average model, autoregressive moving average model, integrated moving average autoregressive model, and so on. Dharyll Prince m et al. [4] (2019) developed an autorepressant integrated moving average (ARIMA) model to analyze the traffic flow dynamics of the Philippines. Sheng Yang Ge et al. [5] (2013) drew an exponential smoothing and trend moving average method. Lingru Cai et al. [6] (2021) introduced the maximum correlation entropy to deduce the Kalman filter to formulate the traffic flow prediction task as well as achieved superior performance. Zhao Liu et al. [7] (2018) introduced a combination of K—nearest neighbor and support vector regression to improve the accuracy. However, in most cases, the traditional statistical model has certain requirements or assumptions for the data, and requires the model itself to have a relatively clear mathematical form. However, in most cases, people are usually unable to make any assumptions about the distribution of data in the real world.

In recent years, with the extensive application of artificial intelligence methods such as machine learning and deep learning in the field of transportation, the prediction of traffic flow has achieved good research results in terms of a nonlinear relationship. Machine learning methods [8] (2022) can analyze complex and diverse data in-depth without any assumptions about the data. Understanding how to deeply analyze complex and diverse data through machine learning and make efficient use of information has become one of the main problems paid attention to by big data. Pan Chengsheng et al. [9] (2022) used the neutral net to achieve traffic prediction. Meanwhile, Lin Guancen et al. [10] (2022) succeeded in traffic prediction based on the traditional machine learning method. As well, Yuen Man Chung et al. [11] (2022) used a competition mechanism multi-objective particle swarm optimization algorithm to solve the traffic flow problem efficiently.

The most important data information is the information based on the time dimension and the space dimension. The traffic flow prediction method based on these two dimensions is deeply studied. Wang Jun et al. [12] (2022) developed a method of automatically obtaining spatial dependence in data, which can automatically obtain the spatial state and spatial dependence using a multi graph advantageous neural network to predict traffic flow in time and space. V é lezserrano Daniel et al. [13] (2021) performed a short-term prediction of traffic flow in Madrid, using different types of neural network architectures with a focus on convolutional residual neural networks. Xinyu Chen et al. [14] (2021) obtained better prediction results after a Bayesian decomposition of multidimensional data. Peixiao Wang et al. [15] (2022) proposed a multi-view bidirectional spatio-temporal network based on the spatio-temporal network. Shaokun Zhang et al. [16] (2022) proposed a graph-based multi-sensor prediction framework which improved the accuracy of prediction

In neural network prediction, long short term memory (LSTM) is widely used in various models, and has achieved good results. Wangyang Wei et al. [17] (2019) realized traffic flow based on AutoEncoder and LSTM. Ali Ahmad et al. [18] (2021) advised a unified dynamic deep spatial temporary neural network model based on progressive neural networks and long short-term memory to simultaneously predict crowd flows in every region of a city. Alkhede et al. [19] (2021) selected three machine learning approaches namely fuzzy logic, long short term memory (LSTM), and decision trees to predict traffic flow. The results show that LSTM has proven to have the best results of the three models. Wang Ke et al. [20] (2021) put forward a short-term traffic flow prediction model based on the attention mechanism and the 1dcnn-lstm network

The model-driven method [21] (2020) is used to build a model based on the understanding of the traffic model, but its accuracy and applicability are limited due to the complexity of the actual traffic environment. The data-driven method focuses on the mapping relationship between data and phenomena, but the demand for data is large, and the understanding and application depth of traffic mechanisms is insufficient. Therefore, this research draws a method based on the combination of multiple linear regression and LSTM. The operation law of intersection traffic is obtained by multiple linear regression on the data of relevant intersections, and predicted in combination with LSTM. Compared with the spatiotemporal graph convolution network, the amount of data is greatly reduced, and the model is simplified when the accuracy is not much different.

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