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Research and application of urban real-time traffic flow prediction based on STARIMA

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***Abstract*—As one of the most basic and important functions in the intelligent transportation system, the related research of intelligent transportation management and control has attracted extensive attention of researchers from all over the world. Good traffic control and guidance are inseparable from accurate and real-time traffic flow prediction, and at the same time, real-time and reliable traffic flow prediction is also the key to the transition of the traffic system from "passive control" to "active control". The extraction and analysis of traffic flow features are inseparable from the support of complete and accurate data sets. This paper considers the correlation between missing data and available spatiotemporal data, as well as the correlation between road network topology and traffic flow, in order to minimize the filling of missing data points In this paper, an optimization method for missing data filling based on spatiotemporal topological map is proposed. Firstly, use the defined "relevant road sections" and "traffic flow correlation levels" to analyze the temporal and spatial correlation of the traffic flow of the road network, and generate a traffic flow prediction map. Traffic flow prediction is performed using an improved space-time auto-regressive moving average model (Space-time Auto-regressive Integrated Moving Average STARIMA). The prediction results show that the algorithm proposed in this paper reduces the prediction time by reducing the number of filling points. At the same time, because the algorithm selects the most relevant traffic section for traffic flow prediction, the prediction accuracy is further improved, and a real-time and effective traffic flow is finally realized. predict.**

Keywords—traffic flow prediction, data padding, spatiotemporal correlation, optimal deployment

I. INTRODUCTION

A. Research background and significance

Transportation is the main driving force for urban development. The rapid development of urbanization has promoted the continuous growth of car ownership in my country. With the expansion of urban space and the lengthening of travel distance, people's dependence on transportation is also increasing. Statistics show that as of the end of December 2021, the number of motor vehicles nationwide has increased by 10.51% year-on-year to 327 million vehicles, including 240 million vehicles. There are 61 cities with more than one million vehicles nationwide. There are 27 cities with more than 2 million vehicles. Facing the surge in the number of cars, road scale and road participants, under the new development background, traffic development is facing new challenges, and urban traffic problems have gradually become prominent. Environmental pollution, traffic congestion and traffic accidents have become the three major problems faced by urban traffic, which seriously restrict the economic development of urban society. In view of the problem of environmental pollution, solid suspended solids are often one of the main reasons for the formation of fog, and the emission of motor vehicle exhaust aggravates the increase of solid suspended solids, which is the main reason for the formation of foggy weather. The large-scale use of fossil fuels not only directly harms It threatens human health, threatens human living environment, and may exacerbate resource depletion and cause energy crisis[1].

An efficient, energy-saving and safe intelligent transportation system can maximize the performance of basic transportation facilities and effectively utilize limited road transportation facilities and resources. As the most basic components of intelligent transportation systems, intelligent traffic control and traffic guidance have always been Research hotspots that are concerned by transportation technology researchers in various countries. However, the key to achieve good traffic control and guidance lies in real-time and accurate traffic flow prediction[2]. The real-time and reliability of traffic flow prediction directly affects the effect of traffic control and traffic guidance. "key. At present, many cities across the country have initially established a traffic information collection, processing and information release system.

B. Research status at home and abroad

Advanced intelligent transportation technology helps to improve road safety, reduce traffic congestion and exhaust emissions, and build a transportation system that is energy-efficient, efficient and has excellent operational performance. To this end, researchers from all walks of life have carried out a large number of related research projects, and have achieved a series of phased good results.

The intelligent transportation system is based on the existing road infrastructure and uses technologies such as communication, big data, artificial intelligence, etc., to solve the problems of traffic congestion, traffic accidents and environmental pollution, and realize the intelligent upgrade of the transportation system. Internationally, there has been relatively mature research and the research momentum is advancing rapidly. Taking the United States as a typical example, in 2010, the United States issued an "Intelligent Transportation Strategy Research Plan", which detailed planning and deployment of intelligent transportation system construction and other issues; The project aims to use on-board equipment, roadside facilities and communication equipment to provide traffic travelers and traffic authorities with real-time and reliable traffic information, including the SafeTrip program: collecting monitoring data from operating fleets in areas with multimodal traffic, And use portable devices to obtain traffic flow data to reasonably plan routes and transfer modes[3].

II. SHORT-TERM TRAFFIC FLOW PREDICTION THEORY AND MODEL METHOD

The urban road system is a complex dynamic system. The analysis of a large number of traffic detector data shows that from the long-term data, the traffic flow usually exhibits periodicity and similarity, while in the short term, it has the characteristics of time-varying, correlation and chaos. The characteristics of current and future traffic changes depend to a large extent on the correlation and influence between traffic flows, and the extraction and analysis of traffic flow features are of great significance for traffic flow modeling, prediction, and control[4].

A. Characteristics of urban traffic flow

1) Characteristics of traffic parameters

Traffic flow parameters are an important basis for guiding and analyzing traffic flow. In traffic flow theory, the parameters of traffic flow can be divided into two types: macro parameters include traffic flow, speed, traffic flow density, etc.; micro parameters such as head spacing, vehicle type, Captain wait. Among them, traffic flow, speed and traffic density are three indicators that are often used to characterize the traffic state.

Traffic flow (Q) refers to the number of traffic entities passing through the observation point or section of a road section within a unit observation time.

$$Q = \frac{N}{T}$$

Among them, N represents the number of traffic entities passing through the observation point within the observation time T.

The speed (v_t) is often regarded as the average speed here, that is, the arithmetic mean of the speed of all vehicles passing through the observation point of a certain road section in a certain time interval.

$$v_t = \frac{1}{N}\sum_{i=1}^{N} v_i$$

Traffic flow density (K), here also refers to the lane space occupancy rate, that is, the ratio of the total length of vehicles to the total length of the road on a certain road section.

$$\mathrm{K} = \frac{\mathrm{A}}{\mathrm{L}}$$

Among them, A represents the total length of the vehicle, and L represents the total length of the road segment.

2) Spatial and temporal characteristics of traffic flow

In recent years, researchers have paid more and more attention to how to build a prediction model that can integrate more spatiotemporal features and even information of the entire transportation network, and study the characteristics of urban traffic flow including spatiotemporal characteristics, which provides a theoretical basis for the prediction and control of traffic flow[5]. Therefore, this section provides an overview of the spatiotemporal properties of traffic flow in order to apply it to the study of problems related to traffic flow analysis and forecasting.

The time characteristic of traffic flow means that in general, the time series of traffic flow has a long-term correlation, that is, the current and future traffic conditions are greatly affected by the historical traffic conditions, and the changes of the time series are related to the changes of the historical time series. relation. As shown in Figure 1, the spatial characteristics of traffic flow focus on the distribution and flow of road vehicles in geographic space. In the urban road network, since any road segment is spatially accessible, this makes the traffic flow more spatially presented. Cross-correlation characteristics, that is, the closer the distance between two road segments in space, the higher the similarity of the traffic flow.

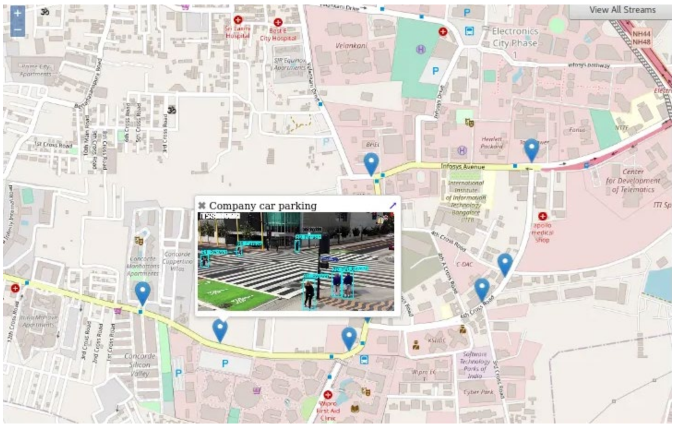

Figure 1 Traffic network topology

The traffic density of the current road segment will affect the traffic flow of other road segments that are spatially adjacent to it in the future time period, and the traffic congestion of the adjacent road segment may also spread to the next time interval. For other road sections far away, this traffic flow propagation law can be measured by correlation[6]. Therefore, a metric for the relationship between time series, the Pearson Product-Moment Correlation Coefficient (PPMCC), is proposed:

$$PPMCC_{xy} = \frac{E\left[(x_t - \mu_x)(y_t - \mu_y)\right]}{\sigma_x \sigma_y}$$

The above formula represents the correlation between two time series x and Y, where μ_x and μ_y represent the mean of the time series x and Y, respectively. However, this metric cannot capture the temporal characteristics of the traffic flow time series, therefore, a new metric is proposed—Coefficient of Determination (COD):

$$CoD_{xy}(k) = 100\left[\frac{E\left[(x_t - \mu_x)(y_{t+k} - \mu_y)\right]}{\sigma_x \sigma_y}\right]^2, k = 0, \pm 1, \cdots$$

In traffic flow prediction, if we consider the traffic information of the predicted road segment x and know the time series of its “neighbor segment” Y, the correlation between the current traffic data of x and the historical spatiotemporal data of Y can provide useful predictions Information. In addition, due to the randomness of road traffic conditions, the larger the scope of the road network that the measurement criterion acts on, the higher the measurement accuracy. The schematic diagram of the spatial propagation of traffic flow is shown in Figure 2.

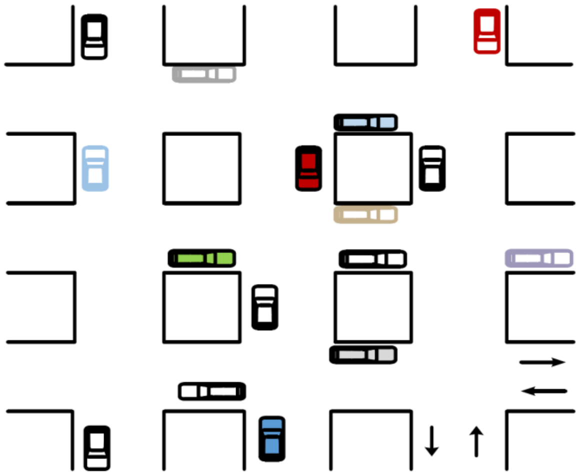

Figure 2 Schematic diagram of spatial propagation of traffic flow

B. Short-term traffic flow prediction model and method

The purpose of short-term traffic flow forecasting is to predict the traffic trend in the next few seconds to several hours. The short-term traffic flow can be divided into time series models and machine learning methods from the way of processing traffic data. The higher the degree of agreement between the flow prediction model and the actual traffic data, the higher the application value of the prediction results. In order to improve the prediction accuracy and the real-time performance of prediction information, short-term traffic flow prediction is usually analyzed from a macro perspective, and generally does not consider the microscopic individual movement characteristics. This section will give an overview of the models related to short-term traffic flow forecasting, and enumerate typical forecasting models[7].

1) Autoregressive Moving Average Model (ARIMA)

In the application of time series, it is first necessary to perform unit root test on the sequence to determine the stationarity of the sequence. If the sequence is non-stationary, it can be transformed into a stationary sequence through multiple differences. The process of performing several differences is called several-order single sequence. If it is for stationary time series modeling, it can be directly represented by the ARMA model, where the ARMA model is as follows:

$$X_t = \sum_{k=1}^{p} \phi_k X_{t-k} + \sum_{k=1}^{q} \theta_k \varepsilon_{t-k} + \varepsilon_t$$

The first term (autoregressive AR) is a linear aggregation of p historical data to establish the relationship between current forecast values and historical data; the second term (moving average MA) is a linear regression of a prior error to determine the current forecast The error relationship with historical data, a represents the size of the sliding window; the last item is the error term, and the error value obeys the Gaussian distribution (white noise). The ARIMA model is expressed as follows:

$$\left(1 - \sum_{k=1}^{p} (\phi_k B^k)\right)(1-B)^d X_t = \left(1 + \sum_{k=1}^{q} (\theta_k B^k)\right)\varepsilon_t$$

2) Seasonal Autoregressive Moving Average Model ((S ARIMA)

The SARIMA model is an improved model of the ARIMA model after considering the seasonal factors of the time series, and it is also one of the most commonly used linear prediction models. The simplified form of the SARIMA model is as follows: $\mathrm{SARIMA}((p,d,q)x(P,D,Q)_S)$, where p is the time lag value of the historical traffic data related to the predicted value, d is the difference order, a is the size of the moving window, p is the number of seasonal autoregressive terms, and D is the The number of seasonal differences, and Q represents the number of seasonal moving average terms. Specifically, the general formula of the SARIMA model is as follows:

$$\Phi_P B^S \phi_p(B)(1-B)^d(1-B^S)^D X_{t=}\theta_q(B)\Theta_q(B^S)\varepsilon_t$$

C. BP neural network method (BPNN)

BPNN is one of the more classic learning methods in neural networks, and it is a multi-layer perception (MLP) structure trained according to error back propagation. Its specific structure is shown in Figure 3 below. BPNN consists of three or more layers of feedforward neural networks, including input layer, hidden layer, and output layer nonlinear neurons. Each node in the figure represents a neuron node, and each column of nodes constitutes a functional layer of NN[8]. Among them, the input layer is used to receive the signals passed to the NN from the outside world, the hidden layer is used to realize its complex functions, and the output layer is used to output information. BPNN is divided into two steps in principle, the first step is forward propagation, and the second step is backward propagation. In the forward propagation process, the training data set is given to the input layer. Then the input layer receives the information and propagates it to the output layer through the hidden layer; in the backward propagation process, the calculation error is propagated back for weight update[9].

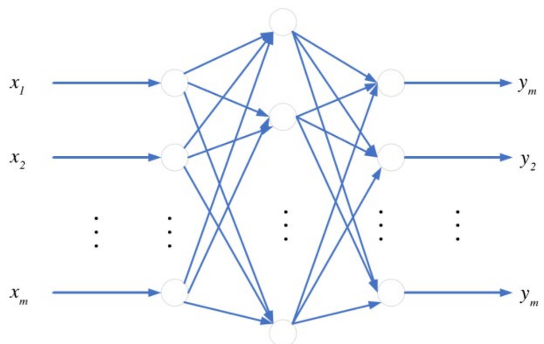

Figure 3 BPNN multi-layer perception training structure

III. TRAFFIC FLOW REAL-TIME PREDICTION METHOD BASED ON MISSING DATA FILLING

In order to solve the impact of missing data on data quality and prediction accuracy in the process of traffic flow prediction in urban road scenarios, this chapter aims at the shortcomings of existing research, comprehensively considers the correlation between missing data and available spatiotemporal data, and minimizes the filling amount as Objective, to propose a real-time traffic flow prediction method based on missing data imputation. On this basis, based on the data collected by the vehicle detector in Taipei, the proposed method is experimentally verified. The results show that the method takes the time spent in the prediction process and the prediction accuracy in the scenario with relatively large data missing. are reduced[10].

A. Traffic flow prediction problem

According to the definition of graph theory, the road topology can be abstracted as Figure 4:

$$G = \{V, E\}$$

Among them, $V = \{V_1, V_2, V_3, \ldots, V_N\}$ represents the set of road segment nodes, which usually refers to the position of the detector observation point; E=$\{e_{ij} = (V_i, V_j) \mid V_i, V_j \in V, i \neq j\}$ represents the set of road segments (where the road segment represents the road between adjacent intersections). In this paper, the urban road network in the experimental object is abstracted as shown in Figure 4.

Figure 4 Actual road network topology

B. STARIMA model with missing data

The STARIMA model is an extension of the ARIMA time series model in the spatial domain:

$$\left(I - \sum_{k=1}^{p} \sum_{l=0}^{\lambda_k} \phi_{k,l} W_l L^k\right) D^d X_t = \left(I - \sum_{k=1}^{q} \sum_{l=0}^{m_k} \theta_{k,l} W_l L^k\right) \varepsilon_t$$

Among them, D represents the difference operation, d is the difference number; p and q represent the time lag of the autoregressive term and the moving average term, respectively; k and l represent the current time and space lag, respectively; ϕ_{kl} and θ_{kl} are autoregressive and moving average. term coefficients. The adjacency matrix w is used to measure the spatial relationship between road segments in the urban road network.

C. Spatiotemporal correlation analysis

In urban traffic forecasting, the spatiotemporal correlation of road segments in a road network is more complex. In order to further capture the spatiotemporal correlation and determine the related road segments in the road network and the propagation range of the traffic flow, we propose two related indicators, the correlated road segment pair and the traffic flow correlation level, to analyze the propagation process of the traffic flow. In order to simplify the analysis and understanding, the following will take the traffic prediction of a certain road section as an example for description as shown in Figure 5.

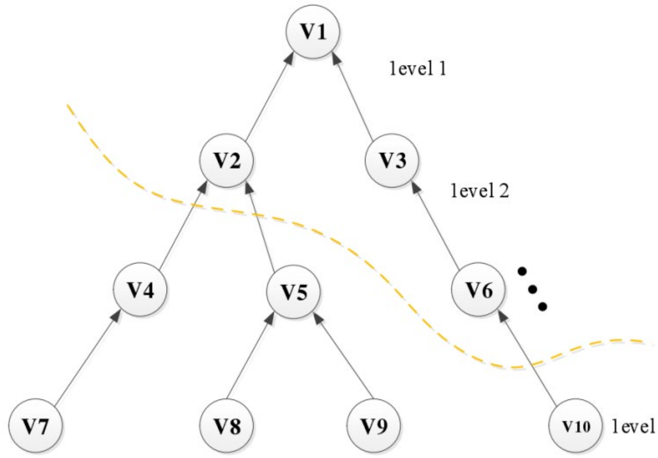

Figure 5 Prediction of road network traffic flow

RRSP: The purpose of spatiotemporal correlation analysis is to select a subset related to the predicted road from the massive traffic variables in the complex road network, which can reduce the complexity of the prediction on the one hand, and improve the prediction accuracy on the other hand. Based on the introduction of the traffic prediction problem in the previous section, firstly find the road “neighborhood” E^{S_i} that has the same traffic law as the road segment. To further analyze the traffic information, the concept of related road segment pairs is introduced. The "neighborhood" of a road Si refers to a road segment that has a propagation association with the road Si in time and space. Any pair of road segments with a "neighbor" relationship in the network are not always geographically adjacent, but they have the most similar traffic patterns. This relationship can be obtained according to the correlation measurement formula in the following formula. RRSPS can be used to determine which roads affect the flow of this target road segment, and extract the trend of future traffic flow from it. For each target road segment S_i, a set of related road segment pairs RRSPS can be derived according to the correlation function.

D. Experiment verification and result analysis

This section presents the experimental results of the prediction performance evaluation. The reliability and effectiveness of the proposed method are verified for the following two scenarios. The first case (Case 1) is to input all missing data for the following imputation prediction. The second case (Case 2) introduces our optimization algorithm to reduce the number of input points before performing the padding and predicting steps. Here, the prediction time is set to 5 minutes.

To evaluate the performance of the method combining the P-MDIO algorithm with the STARIMA model, we compare it with real traffic data and the PPCA-based algorithm with the STARIMA model. Utilize the P-MDIO algorithm to search and select the nearest available data point for prediction. For further analysis, we also compared the RMSE of our proposed algorithm with the PPCA algorithm with different missing ratios, as shown in Fig. 6. The results show that the algorithm has high filling accuracy.

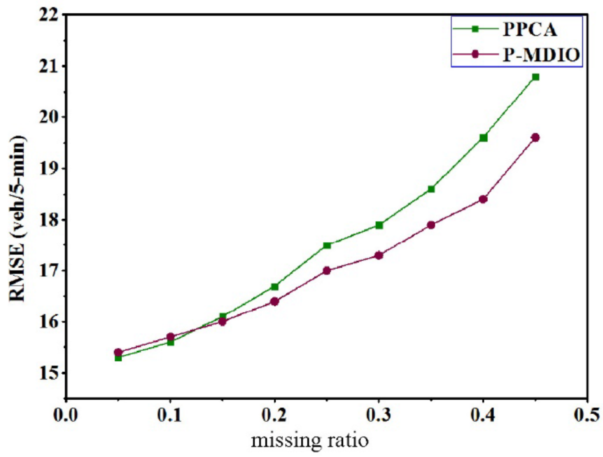

Figure 6 RMSE of different missing filling methods

IV. Conclusion and Prospects

This paper pays attention to the defects in the process of traffic information collection and processing, aiming at real-time and accurate traffic flow prediction, focusing on the following two problems: first, the problem of short-term traffic flow prediction in cities with missing data; second , the observability problem of urban road networks, that is, how to deploy limited detectors to predict traffic information on more road segments. Through the analysis and summary of the research status and deficiencies of the above two issues, the respective improvement methods are proposed and verified by experiments based on the actual road detection data. The main work of this paper is summarized as follows:

(1) Introduce and summarize traffic characteristics, compensation methods for missing traffic data, basic traffic flow prediction methods and models, and commonly used evaluation indicators, and analyze their applicable scenarios, method advantages and disadvantages. At the same time, the sample traffic data is briefly introduced, including data representation, usage instructions, data preprocessing, etc.

(2) Considering that in the case of incomplete traffic data, in view of the problem that data missing in traffic flow prediction affects the prediction accuracy, real-time traffic flow prediction for the entire traffic network is carried out by using spatiotemporal traffic information. Different from the existing idea of filling first and predicting later, we propose a method for optimizing the minimum data filling amount based on PPCA, which updates the required filling point information in real time according to the forecast demand, and re-derives the STARIMA model to predict traffic with missing data. flow. Using vehicle detector data analysis, the method is validated in terms of novelty, reliability, efficiency and accuracy. On the one hand, real-time compensation for missing traffic data can effectively improve the prediction accuracy. On the other hand, considering the impact of the missing data problem, our algorithm took less time to predict future traffic trends without a significant drop in prediction accuracy.

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