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Urban Road Traffic Spatiotemporal State Estimation Based on Multivariate Phase Space–LSTM Prediction

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Abstract: The road traffic state is usually analyzed from a temporal and macroscopic perspective; however, traffic flow parameters, such as density and spacing, can explain the evolution of traffic states from the microscopic perspective and the spatial distribution of vehicles in lanes. In this paper, we attempt to take both temporal and spatial characteristics into consideration simultaneously, and a parameter is defined as the traffic spatiotemporal state of urban road sections to represent the operational status of road traffic, using advanced prediction techniques to estimate its short-term trends. An estimation method is constructed for the traffic spatiotemporal state considering travel times, speeds, and queuing situations from temporal and spatial perspectives. Then, based on Takens' theorem and the single variable phase space, the phase space of multiple traffic parameters is reconstructed and the chaotic characteristics are analyzed. Next, an LSTM prediction model is constructed based on the phase space reconstruction of multiple variables, and the traffic parameters are predicted by empirical analysis. The results show the proposed estimation method has a significantly improved accuracy. Finally, combined with RFID data, the traffic spatiotemporal state of the case section is calculated, which provides a theoretical basis and practical reference for road traffic state evaluations.

Keywords: traffic state estimation; phase space; LSTM prediction

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1. Introduction

The operational status of urban road traffic reflects the degree of use of existing road resources by road users. The road traffic operational status has obvious temporal and spatial distribution characteristics, which are influenced by the method used to determine the operational status. The operational status of roads is generally divided into five levels, and the status is evaluated from different perspectives, such as links, roads, and road networks. Different indicators are selected for evaluation, most commonly the free flow speed, average travel speed, travel time, and other parameters. The evaluation results are distinguished by different colors to visually display the management department's understanding of the road operations. However, from a research perspective, the evaluation results of the road traffic operational status are only static evaluations of quasi-real-time traffic operations based on detection data with a time interval of 5–15 min. Indicators such as speed and travel times are calculated, and the transformation and evolution processes of the macroscopic road traffic operational status must simultaneously be analyzed using other indicators. In addition, the change process of traffic from smooth to congested and then back to smooth at a node position cannot be analyzed without considering the temporal–spatial relationships between vehicles, such as headway and spacing. These relationships can be used to analyze the operational status of nodes at multiple locations and obtain the evolution law of traffic status at node positions, achieving the recognition of operational status for urban roads.

The current urban road traffic operational status assessment criteria focus primarily on the road sections between upstream and downstream detectors, using the vehicle travel time obtained within a certain time interval as the main evaluation index. Although this approach is simple and straightforward, it neglects the uneven distribution of vehicles arriving at adjacent road sections due to the periodic conversion of traffic rules at intersections. Therefore, the travel time index cannot reflect the local spatial evolution characteristics of the traffic operational status, namely, the uneven distribution of traffic flow density in upstream and downstream road sections, simultaneously. To address this issue, the periodic impact of intersections must be introduced into the assessment process by categorizing the arriving traffic into different lane directions. Vehicle arrival and departure times, vehicle-to-vehicle distances, and vehicle speeds should be extracted from detection information to obtain traffic characteristics such as headway and spacing. Microscopic traffic flow theory should be applied to analyze the inaccurate assessment of the traffic operational status caused by the uneven distributions of traffic density in upstream and downstream road sections.

Considering the nonlinear characteristics of detection data time series, a comprehensive prediction model should be developed based on a single parameter, such as the travel time, and incorporate microscopic traffic flow parameters. This involves reconstructing a multivariable space to analyze the nonlinear characteristics of traffic flow parameters. Based on this, a multivariable prediction model can be constructed to obtain the time-based evolution of the traffic operational status, estimate the congestion duration, estimate the spatial distribution of the traffic operational status, and determine the length of the affected road sections.

Phase space reconstruction is an important method for analyzing nonlinear time series and can restore the attractor of a dynamic system in a high-dimensional space. The reconstructed phase space represents the dynamic characteristics of the time series as the physical meaning of the original time series is weakened. Therefore, multivariable phase space reconstruction can be used to integrate multisource data.

The single physical quantity of traffic flow parameters has chaotic characteristics. When comprehensively analyzing traffic conditions, multiple traffic parameters and physical quantities must be analyzed together, that is, from the perspective of a comprehensive space–time analysis. However, when combined with the function of chaotic parameters, the orbit characteristics of multiple chaotic variables change, which affects the chaotic prediction accuracy of space–time parameters. Reducing or avoiding this requires further research.

The main issue in this paper is the presentation of the methodology for solving the spatial–temporal state of traffic in city road sections and predicting trends. To analyze the road operational status from a microscopic perspective, we first start with considering the time dimension. By using microscopic parameters such as the vehicle travel time, speed, headway, and spacing and combining them with mathematical relationships of traffic flow parameters, a microscopic analysis function for traffic operation is constructed by considering the state of waiting in line. Combined with analyzing the non-linear characteristics of microscopic parameters and forecasting methods, the phase space is reconstructed and short-term prediction is conducted on the reconstructed phase space matrix to obtain the prediction result of the traffic spatial–temporal state.

The structure of the paper is as follows. Section 2 presents the related work regarding spatiotemporal operation characteristics of the traffic state, multivariate phase space analysis, its applications in traffic flow, and deep learning methods for traffic flow parameter prediction applications. Section 3 presents the methodology for the spatial–temporal state of traffic considering the travel time, speed, and the state of waiting in line from a temporal and spatial perspective. Section 4 presents the datasets used for the evaluation of the method and discusses the experimental results and future work. Finally, Section 5 concludes the paper.

2. Literature Review

2.1. Analysis of Spatiotemporal Operation Characteristics of the Traffic State

Much research has been conducted on typical traffic state classification parameters and methods, as shown in Table 1. Felix et al. [1] analyzed the spatiotemporal distribution characteristics of chronic traffic congestion by simplifying a complex traffic network into the most frequently congested parts (clusters) based on real-time collected data and introducing clustering methods. Ryo Inoue et al. [2] proposed a method based on frequent pattern mining in information science for analyzing traffic sensor data to understand traffic congestion patterns in cities. The feasibility and effectiveness of the proposed method were evaluated through an analysis of traffic sensor data in Okinawa (Japan). Rajvi Kapadia [3] created a model for mining traffic period patterns that accounted for the impact of monsoons on road traffic, presenting an overall traffic scenario analysis and more accurately analyzing the traffic patterns of developing cities with a high population density such as Mumbai. Based on the work by Qingdao, Sun [4] combined traffic performance index (TPI) data with a hierarchical clustering algorithm to extensively study traffic congestion in urban commercial districts. In a study in Beijing, Lei et al. [5,6] constructed a traffic state classification system based on the flow, speed, time occupancy, and road network redundancy and analyzed the system using an improved fuzzy clustering algorithm. Clustering of actual traffic parameters detected in some areas of the Beijing expressway network allowed the states of traffic flow data to be determined. Liu et al. [7] used floating vehicle data and real-time traffic data to analyze the traffic status of schools around roads through spatiotemporal clustering, revealing the distribution characteristics of traffic status around schools in Beijing. Fabritiis et al. [8] estimated traffic speeds from GPS traces and proposed algorithms based on artificial neural networks and pattern matching for short-term travel speed predictions in Italy. Wu et al. [9] considered the impact of road grades on congestion indicators, selected the INRIX road congestion index system, used taxi trajectory data to calculate the road congestion index, and proposed an abnormal judgment method for the road congestion index and a congestion index correction method based on regional continuity. He et al. [10] introduced the spatiotemporal cumulative index of traffic congestion to identify and quantitatively analyze the operational status of regional transportation; established a functional relationship between congestion sources and congestion evaluation points to construct a visual model; used gradient direction histograms and principal component analysis to extract features from traffic operation status data; and used the Gaussian mixture clustering method to cluster the feature data and classify the spatial distribution pattern of regional traffic congestion. D'Andrea et al. [11] presented an expert system for detecting traffic congestion and incidents from real-time GPS data collected from GPS trackers or drivers' smartphones. Kan et al. [12] proposed an approach for detecting traffic congestion from taxis' GPS trajectories at the turn level by analyzing features of GPS trajectories and identifying valid trajectory segments; they also detected congested trajectory segments of three different intensities.

In addition, many scholars have explored traffic congestion from different perspectives. For example, Gao et al. [13] explored and analyzed the spatiotemporal distribution characteristics, laws, and causes of traffic congestion in Xuchang city based on the real-time traffic data over one week.Sun et al. [14] primarily studied the spatiotemporal distribution characteristics of traffic congestion caused by traffic accidents on urban roads, characterized the spatiotemporal features of traffic states from the perspective of congestion, and established a congestion determination model based on speed differences. Anbaroğlu et al. [15] proposed an NRC (non-recurrent congestion event) detection methodology to support the accurate detection of NRCs in large urban road networks by substantially estimating high link journey times on adjacent links.

Overall, significant progress has been made in the traffic congestion field worldwide, encompassing a variety of methods and fields. These studies provide important references for transportation planning and management and help to improve traffic congestion in cities.

Table 1. Data and parameters for traffic state classification.

No.	Data and Parameters	Methods	Typical Research
1	Traffic performance index (TPI) Data From Qingdao, China	Hierarchical clustering	Sun et al. [4]
2	Volume, speed, occupy, road network redundancy from urban expressway	Fuzzy clustering	Lei et al. [5,6]
3	Float car GPS and real-time data from Beijing, China	Temporal–spatial clustering	Liu et al. [7]
4	Float car data from metropolitan areas in Italy	Pattern matching	Fabritiis et al. [8]
5	Taxi trajectory data from Fuzhou, China	Abnormal judgment	Wu et al. [9]
6	Taxi data from Guangzhou, China	Gaussian mixed clustering	He et al. [10]
7	GPS traces from the city of Pisa	Speeds data mining	D'Andrea [11]
8	Taxis' GPS data from Wuhan, China	Turn-level clustering	Kan et al. [12]

2.2. Multivariate Phase Space Analysis and Its Applications

The complex nonlinear characteristics of road traffic operations make scientifically and accurately describing the traffic operation status with a single parameter difficult. Therefore, a rapidly developing technical method based on multivariate variable analysis has been proposed. Its theoretical basis is the phase space reconstruction technology based on a single variable, which constructs phase space reconstruction theory and a method for multiple variables. This method, based on phase space reconstruction technology, can more comprehensively reveal the mutual relationships between multiple traffic variables, thereby facilitating more accurate traffic operation status analyses. Traditional multivariate variable phase space reconstruction and prediction methods are shown in Table 2. Wang [16] proposed a coarse-grained algorithm for time series mapping to complex networks by combining phase space reconstruction and rough set technology. This algorithm transformed time series into complex networks to more accurately describe the evolution characteristics of time series. Li [17] proposed a multidimensional chaotic time series prediction method based on Bayesian theory, which integrated traffic measurement values (speed, occupancy, and flow) from different data sources through phase space reconstruction. Qian et al. [18] established a traffic flow prediction model based on phase space reconstruction and Kalman filtering theory to improve the urban traffic flow prediction accuracy. This model could effectively reflect the essential characteristics of traffic flow. Yang [19] used the maximum Lyapunov exponent to analyze the predictability of traffic flow and then reconstructed the phase space. The reconstructed phase points were introduced into the Kalman filter equation as the initial state points to establish a short-term traffic flow prediction model based on phase space reconstruction. Cheng [20] used multiple measurement parameters, such as the average speed, average occupancy, and average traffic flow, to describe a transportation system. A multisource and multi-measurement traffic flow prediction model was constructed using chaos theory and the support vector regression method. Chaotic time series of multiple measurements were integrated into a multidimensional phase space through phase space reconstruction by selecting embedding dimensions and delay times. Tang [21] proposed a hybrid prediction model (GQPSO-WNN) based on phase space reconstruction to quantitatively analyze the chaos characteristics and predictability of traffic flow changes. The advantages of the genetic algorithm (GA) and quantum particle swarm optimization (QPSO) were cleverly combined to enhance the model performance by optimizing the wavelet neural network parameters.

Table 2. Traditional methods of multivariate phase space reconstruction and prediction.

No.	Data	Main Methods	Typical Research
1	period time series	Complex network	Wang [16]
2	speed, occupancy, and flow	Bayes theory and phase space reconstruction theory	Li [17]
3	traffic flow data	Phase space reconstruction and Kalman filtering theory	Qian et al. [18]; Yang et al. [19]
4	speed, occupancy, and flow	Support vector machine and chaos theory	Cheng [20]
5	traffic flow time series	Phase space reconstruction and genetic algorithm (GA) and quantum particle swarm optimization with the wavelet neural network	Tang [21]

Shang [22] constructed a short-term traffic flow prediction model based on phase space reconstruction and regularized extreme learning machines to improve the short-term traffic flow prediction accuracy. The optimal time delay and embedding dimension of the traffic flow time series were determined using the C-C algorithm, and the phase space was reconstructed. The G-P algorithm was used to calculate the correlation dimension of the sequence, and chaos characteristics were identified for short-term traffic flow sequences. Wang et al. [23] introduced a multi-time series reconstruction method based on data fusion. A social cognitive algorithm and adaptive weighted fusion estimation were used to optimize the weight of each component. The phase space was reconstructed by fusing different phase spaces through data fusion, providing a new idea for the data fusion of heterogeneous sensors. To address the large number of monitoring variables and high redundancy in chemical production systems, Zhao et al. [24] proposed a multisource data fusion method based on phase space reconstruction. The parameters of phase space reconstruction were obtained using the mutual information and Cao methods, providing new insights into solving multisource heterogeneous sensor data fusion problems. Thonhofer et al. [25] presented a modular macroscopic traffic model with two traffic light formulations, and the proposed model allowed arbitrary functional forms of the fundamental diagram defined by a small number of parameters; then, the moving density gradients (jam fronts) were represented accurately, and the model parameters were physically meaningful and could readily be estimated from measurement data. Li [26] aimed to improve the accuracy of short-term traffic flow predictions by studying a prediction model based on phase space reconstruction and particle swarm optimization Gaussian process regression. To overcome the nonlinearity, complexity, and randomness of traffic flow time series, the phase space was reconstructed based on chaos theory to obtain the best delay time and embedding dimension of the original time series, which were used as the input–output data set of the model to maintain the same dynamic characteristics as the original data. Hou [27] proposed a method for predicting connected traffic flow data with chaotic characteristics by using an improved phase space reconstruction method to reveal chaotic dynamics in data and a hybrid deep learning model to extract features from phase space data and optimize model parameters, improving the prediction results.

2.3. Deep Learning Methods for Traffic Flow Parameter Prediction Applications

Traffic flow parameter prediction is an important component of urban traffic management and planning, and it is crucial for alleviating traffic congestion, improving road usage efficiency, and optimizing transportation system operations. Some researchers have combined machine learning with traditional linear methods, including the K-nearest neighbor algorithm (KNN), support vector regression (SVR), K-means, and artificial neural network (ANN) models, to predict traffic flow parameters. In recent years, the rapid development of deep learning technology has attracted widespread attention to its applications in traffic flow parameter prediction. Deep learning can automatically learn feature representations from large-scale traffic data by constructing complex neural network structures, thereby improving the accuracy and robustness of predictions. Researchers have applied deep learning to traffic flow parameter prediction, achieving significant results. These deep learning models can obtain more accurate prediction results than early machine learning models and statistical models. For time series data such as traffic flow, recurrent neural networks (RNNs) have been used to fully extract the information of each time step during spatial–temporal feature extraction. Typical multivariate variable phase space reconstruction and prediction methods are shown in Table 3. Liu et al. [28] presented a method for short-term traffic flow prediction based on an attention model that can extract spatiotemporal features and understand the influence of each unit of data. Zhang et al. [29] constructed a traffic flow prediction model based on image Motif-GCRNN, capturing spatiotemporal dependencies in road networks through graph convolutional learning. Yang et al. [30] proposed a stacked autoencoder Levenberg–Marquardt model to improve the prediction accuracy by learning traffic flow features through layer-by-layer unsupervised learning. Wu et al. [31] proposed a DNN-based traffic flow prediction model (DNN-BTF) that fully utilized the periodicity and spatiotemporal characteristics of traffic flows using convolutional neural networks and recurrent neural networks to extract spatial and temporal features. Du et al. [32] proposed an adaptive multimodal deep learning model, HMDLF, combining a convolutional neural network (CNN) and gated recurrent unit (GRU) models to capture local trends and long-term dependencies in traffic data, reducing the computational complexity. Tan et al. [33] proposed a new short-term traffic flow prediction method based on dynamic tensor completion (DTC), where traffic data were represented as dynamic tensor patterns. This method was able to capture more traffic flow information, including the time variability, spatial features, and multimodal periodicity, than traditional methods. A DTC algorithm was designed to use multimodal information for low-rank constraint prediction of traffic flow.

Table 3. Recent methods on multivariate predictions.

No.	Data	Main Methods	Typical Research
1	traffic speed	CNN combined with LSTM and attention mechanisms	Liu et al. [28]
2	traffic speed	Graph convolutional recurrent neural network	Zhang et al. [29]
3	traffic flow data from the M6 freeway in the U.K.	Self-encoded Levenberg–Marquardt model	Yang et al. [30]
4	PeMS database	Mixed methods on convolutional recurrent neural network	Wu et al. [31]
5	flow, speed, journey time from UK	CNN and GRU	Du et al. [32]
6	PeMS database	Dynamic Tensor Completion	Tan et al. [33]

Polson et al. [34] developed an innovative deep learning architecture for predicting traffic flow. The architecture combined linear models with a series of tanh layers to address the challenges of sharp nonlinear spatiotemporal effects produced by transitions between free flow, congestion, recovery, and gridlock. Kumar et al. [35] used the predictive scheme of seasonal ARIMA (SARIMA) models to overcome data availability issues and used limited input data for short-term traffic flow prediction. Lopez-Garcia et al. [36] proposed a method for optimizing the elements of fuzzy rule-based system (FRBS) hierarchies using a GA and cross-entropy (CE) hybrid, called GACE, for short-term traffic congestion prediction. Chen et al. [37] proposed a chaotic prediction method based on the Lyapunov exponent for traffic flow characteristics with chaos. Dong et al. [38] proposed an end-to-end trainable unified model that combines an autoencoder and a random forest to construct a random decision tree model for guiding parameter learning. Liao et al. [39] used Dest-ResNet to correct the original traffic speed prediction errors and solved the time series relationship problem caused by crowdsourcing map queries. Shao et al. [40] used a long short-term memory (LSTM) network and other models for traffic flow prediction. This model further improved the RNN and addressed gradient explosions caused by missing data in simple RNNs. Ma et al. [41] applied LSTM networks for traffic speed prediction, demonstrating that the

LSTM structure can capture long-term time dependencies in traffic data and overcome the vanishing gradient problem by using memory blocks, demonstrating excellent performance in time series prediction with long-term dependencies. Zhang et al. [42] proposed a tree-based ensemble method that improved the performance of highway section travel time predictions by considering variables derived from historical data. Additionally, gradient boosting tree methods have also been developed, revealing hidden patterns in travel time data and improving the accuracy and interpretability of models. Deep learning technology has tremendous potential for traffic flow prediction. Future research could further explore deep-learning-based traffic flow prediction methods to improve the efficiency of traffic management and reduce the negative impacts of urban traffic problems.

In summary, numerous methods have been proposed to address traffic operating status estimation and classification. A comparative analysis of these methods has revealed the following characteristics: First, many studies focus on the parameters of either the time or spatial dimensions to conduct state classification or recognition research, and the selected methods rely primarily on pattern recognition or clustering methods. Second, prediction and estimation methods based on multivariate variable reconstruction have been continuously developed, with classic theories such as Bayesian theory, Kalman filters, support vector machine, and complex networks being applied widely. Additionally, with the rapid development of neural networks, deep learning, and other technologies, multivariate phase space reconstruction prediction and estimation methods have gradually become research hotspots. Third, the application of deep learning technology has improved traffic parameter prediction accuracy, but a single neural network type can capture only the features of either the time dimension or spatial dimensions of traffic data, and the predicted results cannot reflect the characteristics of traffic operation changes in multiple dimensions and levels.

In this paper, we combine the evaluation criteria for urban road traffic status with parameters such as the headway, vehicle spacing, queue length, and delay time. We analyze the formation of congestion from the perspective of traffic flow microparameters (changes in vehicle speed and headway distance, combined with analysis using car-following models), the congestion duration (changes in headway time series and the chaotic characteristics of headway time series), and the congestion spread (queue length and the accumulation of headway distance to obtain vehicle platoon length). Based on Takens' theorem, we analyze the nonlinear characteristics of the single variable phase space reconstruction of traffic parameters, construct a multivariate variable phase space, and obtain the embedding dimension and delay time of multivariate variable time series. Then, we combine data-driven and deep learning methods to construct a fusion prediction model of multivariate variable phase space reconstruction. Using the analysis results of the spatiotemporal operating patterns of road traffic and the multivariate variable phase space prediction model on real road data, we conduct empirical research to evaluate the model's prediction performance.

3. Methodology

The traffic data, such as traffic volume, density, and speed, are typical macroscopic data, while the microparameters are the headway and vehicle spacing. Integrating these two types of data is the basis for a multilevel analysis of the traffic operating status. We mainly use data from section detection, but we were able to obtain the driving paths of vehicles to integrate microscopic data and macroscopic data at the data collection end.

3.1. Basic Definitions of Traffic Spatiotemporal Parameters

A comprehensive analysis of the travel time and the travel time under free-flow speed can be used to determine the traffic operating status, as shown in the first part of Equation (1), which judges the traffic operating status from the time dimension, or in a macroscopic sense. In urban road conditions, the interactions between vehicles, such as vehicle–vehicle spacing parameters and traffic control, are important factors leading to changes in traffic flow status. As shown in Figure 1, vehicles are distributed within the lanes upstream and downstream of the intersection. Therefore, a comprehensive analysis of vehicle queue lengths and travel time parameters can be used to evaluate the road traffic operating status.

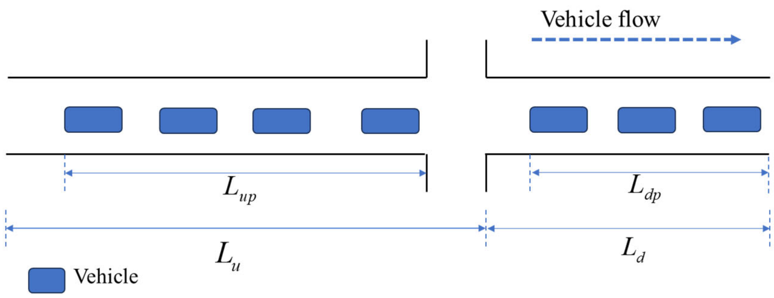


Figure 1. Vehicle distribution in urban lanes.

Defining the traffic spatiotemporal state as TP, using the traffic state evaluation method based on the free flow speed and travel time, and accounting for the uneven distribution of road density, the improved evaluation formula for the length of the vehicle queue in the upstream and downstream sections of the intersection during the analysis period is given by Equation (1):

$$\begin{aligned} TP &= a \cdot \frac{T_v - T_{vf}}{T_{vf}} + (1-a) \cdot \left(\frac{L_u}{L_u + L_d} \cdot \frac{L_{up}}{L_u} + \frac{L_d}{L_u + L_d} \cdot \frac{L_{dp}}{L_d} \right) \\ &= a \cdot \frac{T_v - T_{vf}}{T_{vf}} + (1-a) \cdot \left(\frac{L_{up}}{L_u + L_d} + \frac{L_{dp}}{L_u + L_d} \right) \\ &= a \cdot \frac{T_v - T_{vf}}{T_{vf}} + (1-a) \cdot \frac{L_{up} + L_{dp}}{L_u + L_d} \end{aligned} \tag{1}$$

where α is the weight of the travel time parameter, T_v is the travel time of the road section, T_{vf} is the travel time of the road section under free flow speed, L_u is the length of the upstream road section, L_d is the length of the downstream road section, L_{up} is the length of the vehicle queue in the upstream road section, and L_{dp} is the length of the vehicle queue in the downstream road section.

3.2. Traffic Spatiotemporal Parameters with Queuing and Travel Time

Based on the microscopic parameters of the vehicle flow combined with queuing theory methods, the waiting time and queue length of vehicles at the entrance lane of the intersection are obtained. That is, the basic theory of queuing is used to determine the queue situation in the upstream and downstream sections of the intersection. Accounting for the mathematical relationship between queue length, vehicle number, and vehicle average spacing, as shown in Equation (2), and using the mathematical relationship between vehicle number and density and road length, Equation (1) can be rewritten as Equation (3).

$$L = \overline{h}_s \cdot N = \overline{h}_s \cdot k \cdot l \tag{2}$$

$$\begin{aligned} TP &= a \cdot \frac{T_v - T_{vf}}{T_{vf}} + (1-a) \cdot \left(\frac{L_u}{L_u + L_d} \cdot \frac{L_{up}}{L_u} + \frac{L_d}{L_u + L_d} \cdot \frac{L_{dp}}{L_d} \right) \\ &= a \cdot \frac{T_v - T_{vf}}{T_{vf}} + (1-a) \cdot \left(\frac{L_{up}}{L_u + L_d} + \frac{L_{dp}}{L_u + L_d} \right) \\ &= a \cdot \frac{T_v - T_{vf}}{T_{vf}} + (1-a) \cdot \frac{L_{up} + L_{dp}}{L_u + L_d} \\ &= a \cdot \frac{T_v - T_{vf}}{T_{vf}} + (1-a) \cdot \frac{\overline{h}_{sup} \cdot k_{up} \cdot L_u + \overline{h}_{sdp} \cdot k_{dp} \cdot L_d}{L_u + L_d} \end{aligned} \tag{3}$$

where k_{up} is the traffic density in the upstream section, k_{dp} is the traffic density in the downstream section, $\overline{h}_{sup}$ is the average headway of traffic in the upstream section, and $\overline{h}_{sdp}$ is the average headway of traffic in the downstream section.

Based on the relevant literature [43], the travel time of a road segment can be considered as the sum of the typical vehicle travel time and the travel time fluctuation of the road segment, as shown in Formula (4). Then, Formula (3) can be rewritten as Formula (5).

$$\overline{T} = T_1 + \frac{1}{n}\sum_{i=2}^{n}(\tau_{d1i}) - \frac{1}{n}\sum_{i=2}^{n}(\tau_{u1i}) \tag{4}$$

$$TP = a \cdot \frac{T_1 + \frac{1}{n}\sum\limits_{i=2}^{n}(\tau_{d1i}) - \frac{1}{n}\sum\limits_{i=2}^{n}(\tau_{u1i}) - T_{vf}}{T_{vf}} + (1-a) \cdot \frac{\overline{h}_{sup} \cdot k_{up} \cdot L_u + \overline{h}_{sdp} \cdot k_{dp} \cdot L_d}{L_u + L_d} \tag{5}$$

3.3. The Traffic Spatiotemporal Parameters Considering Density and Headway

In Figure 2, the length of the road section is denoted by L, the number of vehicles is N, and the corresponding traffic density is k. The intervehicle distance is d_i, the headway between the first vehicle and the preceding vehicle is d_{out}, and the headway between the last vehicle and its following vehicle is d_{in}. The relationship between density, vehicle number, headway, road length, d_{out}, and d_{in} can reveal the following.

$$k = \frac{N}{L} \tag{6}$$

$$L = \sum_{N} d_i + \Delta = \sum_{N} d_i + \beta_1 d_{out} + \beta_2 d_{in} \tag{7}$$

where β_1 and β_2 are weight parameters of the distance at the downstream exit position and upstream entrance position of the road section, respectively, with a value range of [0, 1].

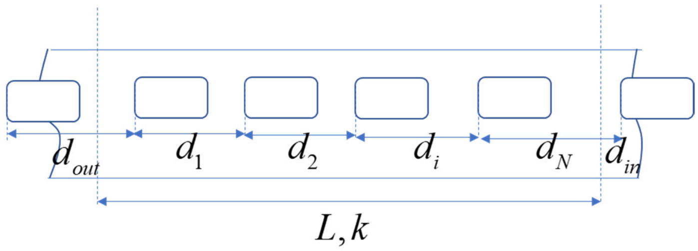


Figure 2. Relationship between density and headway.

Formulas (6) and (7) are transformed to obtain Formula (8), the reciprocal of Formula (8) is taken to obtain Formula (9), and the reciprocal is transformed to obtain Formula (10).

$$k = \frac{N}{\sum\limits_{N} d_i + \beta_1 d_{out} + \beta_2 d_{in}} \tag{8}$$

$$\frac{1}{k} = \frac{\sum\limits_{N} d_i + \beta_1 d_{out} + \beta_2 d_{in}}{N} = \frac{\sum\limits_{N} d_i}{N} + \frac{\beta_1 d_{out}}{N} + \frac{\beta_2 d_{in}}{N} \tag{9}$$

$$\frac{\sum\limits_{N} d_i}{N} = \frac{1}{k} - \frac{\beta_1 d_{out}}{N} - \frac{\beta_2 d_{in}}{N} \tag{10}$$

The average headway and density of vehicles within a road segment are not entirely inversely proportional to each other, which is similar to the conclusion obtained in the literature [44]. According to Formula (10) and the definition of headway, Formula (11) is obtained, which is the product of density and headway.

$$k \cdot \overline{h}_s = \frac{N}{\sum\limits_{N} d_i + \beta_1 d_{out} + \beta_2 d_{in}} \cdot \frac{1}{N}\sum_{N} d_i = \frac{1}{1 + \beta_1 \frac{d_{out}}{\sum_{N} d_i} + \beta_2 \frac{d_{in}}{\sum_{N} d_i}} \tag{11}$$

Combining Formula (5) and Formula (11), the calculation formula for the traffic spatiotemporal state is obtained, as shown in Formula (12).

$$\begin{aligned} TP &= a \cdot \frac{T_1 + \frac{1}{n}\sum_{i=2}^{n}(\tau_{d1i}) - \frac{1}{n}\sum_{i=2}^{n}(\tau_{u1i}) - T_{vf}}{T_{vf}} + (1-a) \cdot \frac{\overline{h}_{sup} \cdot k_{up} \cdot l_{up} + \overline{h}_{sdp} \cdot k_{dp} \cdot l_{dp}}{L_u + L_d} \\ &= a \cdot \frac{T_1 + \frac{1}{n}\sum_{i=2}^{n}(\tau_{d1i}) - \frac{1}{n}\sum_{i=2}^{n}(\tau_{u1i}) - T_{vf}}{T_{vf}} \\ &+ (1-a) \cdot \frac{\frac{1}{1+\beta_{1-up}\frac{d_{out-up}}{\sum_N d_{i-up}} + \beta_{2-up}\frac{d_{in-up}}{\sum_N d_{i-up}}} \cdot L_u + \frac{1}{1+\beta_{1-dp}\frac{d_{out-dp}}{\sum_N d_{i-dp}} + \beta_{2-dp}\frac{d_{in-dp}}{\sum_N d_{i-dp}}} \cdot L_d}{L_u + L_d} \end{aligned} \quad (12)$$

3.4. Characteristics of Headway in the Traffic State

When the traffic volume on the road is relatively low, the headway is large and the density is small. Drivers can freely choose their driving speeds. As the traffic volume increases, the headway decreases and the density increases, with vehicles interacting with each other. As the traffic density further increases, vehicles become congested, the speed decreases, and the driving freedom is reduced. Vehicles move and stop repeatedly, approaching a stationary state.

The car-following model bridges individual vehicles and the overall traffic flow, so the micro characteristics of traffic flow through car-following models have become an important research topic. Analyzing the average headway of car-following behavior allows the road capacity to be estimated. The classic car-following model states that the minimum headway is related to the vehicle length, rear vehicle speed, front vehicle speed, and minimum safe headway time.

In the car-following models proposed by Reuschel (1950) and Pipes (1953), the vehicle length was assumed to be 20 ft and the minimum headway time was assumed to be 1.36 s, which was the minimum reaction time. The car-following characteristics are as follows:

$$\begin{aligned} d_{\min} &= 1.36u_{n+1}(t) + 20 \\ h_{\min} &= 1.36 + 20/u_{n+1}(t) \end{aligned} \quad (13)$$

The car-following theory proposed by Forbe (1958) suggests that the gap between the front and rear cars must be greater than the distance traveled during the rear car's reaction time, i.e.,

$$h_{\min} = \Delta t + \frac{L_n}{u_n(t)} \quad (14)$$

The reaction time is related to factors such as the driver's age, driving experience, gender, and situational awareness, and typically ranges from 0.4 to 2 s [45]. Thus, we assumed a vehicle length of 20 ft and an average reaction time of 1.5 s,

$$\begin{aligned} d_{\min} &= 1.5u_n(t) + 20 \\ h_{\min} &= 1.5 + 20/u_n(t) \end{aligned} \quad (15)$$

Newell approximated the actual spatiotemporal trajectory of a vehicle as a piecewise linear trajectory line, and the relationship between headway and speed is approximately linear.

$$d_i(t) = s_i + v_i(t)\tau_i \quad (16)$$

Based on the Newell model, we convert the spacing into headway time, speed, and the linear sum of the minimum safe distance to calculate the headway used in Formula (12).

3.5. LSTM Prediction of Multivariate Traffic Parameters Based on Phase Space Reconstruction

Using multivariate traffic parameters that describe the spatiotemporal state of traffic, a phase space of the traffic state is constructed. Based on historical time series data of multiple variables, the delay time and embedding dimension used for reconstructing the phase space are calculated. Then, the learning ability of LSTM is utilized to predict the changing values of multiple variables and calculate the value of the traffic spatiotemporal state.

There exists a function such that the phase points in the constructed phase space evolve according to this function, thereby enabling time series prediction. In this paper, the reconstructed phase points are used as input, and the last dimension of the traffic parameter of the next phase point is used as output.

Input:

$$\begin{gathered} D_1 = \left(x_{1,1}, \ldots, x_{1,1+(d_1-1)\tau_1}, \ldots, x_{3,1}, \ldots, x_{3,1+(d_3-1)\tau_3}\right) \\ D_2 = \left(x_{1,2}, \ldots, x_{1,2+(d_1-1)\tau_1}, \ldots, x_{3,2}, \ldots, x_{3,2+(d_3-1)\tau_3}\right) \\ \vdots \\ D_{L-1} = \left(x_{1,L-1}, \ldots, x_{1,L-1+(d_1-1)\tau_1}, \ldots, x_{3,L-1}, \ldots, x_{3,L-1+(d_3-1)\tau_3}\right) \end{gathered} \tag{17}$$

Output:

$$\begin{gathered} Y_1 = x_{1,1+(d_1-1)\tau_1+1} \\ Y_2 = x_{1,2+(d_1-1)\tau_1+1} \\ \vdots \\ Y_{L-1} = x_{1,L-1+(d_1-1)\tau_1+1} \end{gathered} \tag{18}$$

Various forms of the evolution function F are used in evolution, including machine learning methods such as support vector machines and methods based on the physical meaning of chaotic parameters, such as the maximum Lyapunov index [32].

4. Data and Examples

4.1. Urban Road RFID Data Processing and Extraction

In this paper, we extract the vehicle traffic data recorded by RFID on Nanjing urban roads in December 2015. The distribution of the collected base stations is indicated by the green circles in Figure 3. Due to issues such as information transmission and database storage abnormalities, some abnormal data were collected by some base stations. Therefore, in the data analysis section, only valid vehicle passage data from the collected base stations were selected. Taking the data from December 2nd as an example, the license plate matching method was used to extract the vehicle passage records for each base station and generate data sets of vehicle speeds, headways, and travel times.

Three detection devices, 6269, 6271, and 6273, were selected as the analysis case data source, as shown as the red point in Figure 4, encompassing a total length of 660 m, where the traffic direction was shown as the red arrow. Each detection device can collect driving data from three lanes in the same direction, including basic data such as driving speed, vehicle lane, license plate, and passing time.

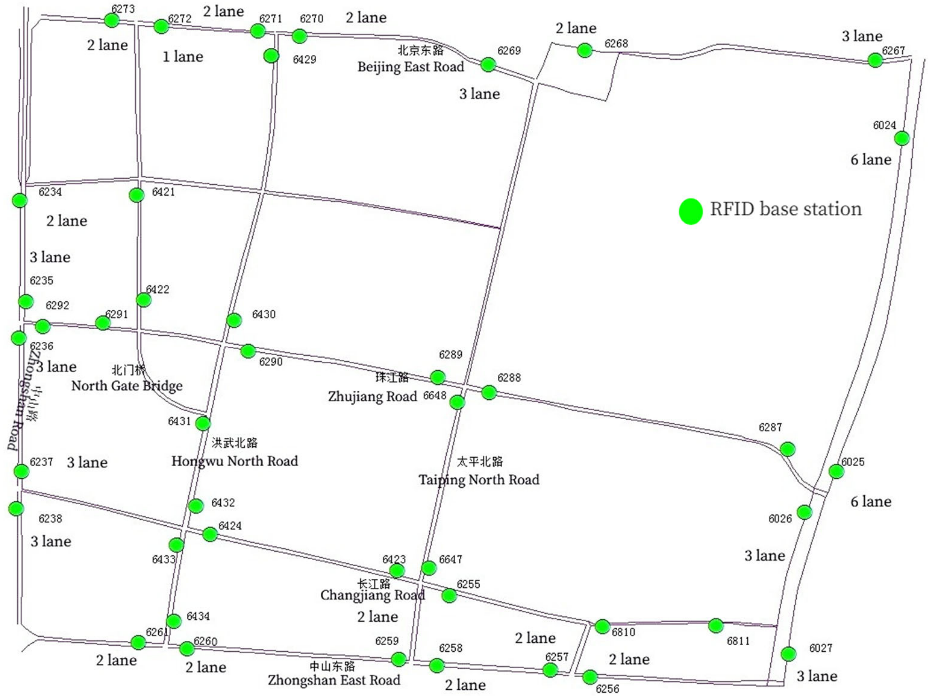


Figure 3. Distribution of RFID base stations on urban roads in Nanjing.

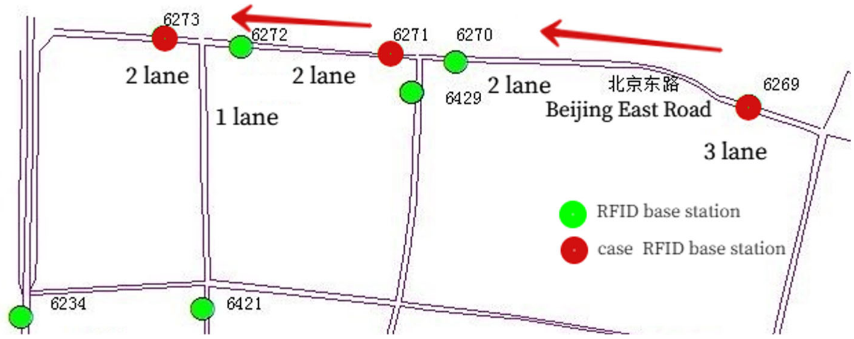


Figure 4. Typical RFID base station distribution in the selected section.

4.2. Analysis of Multivariate Traffic Parameter Characteristics

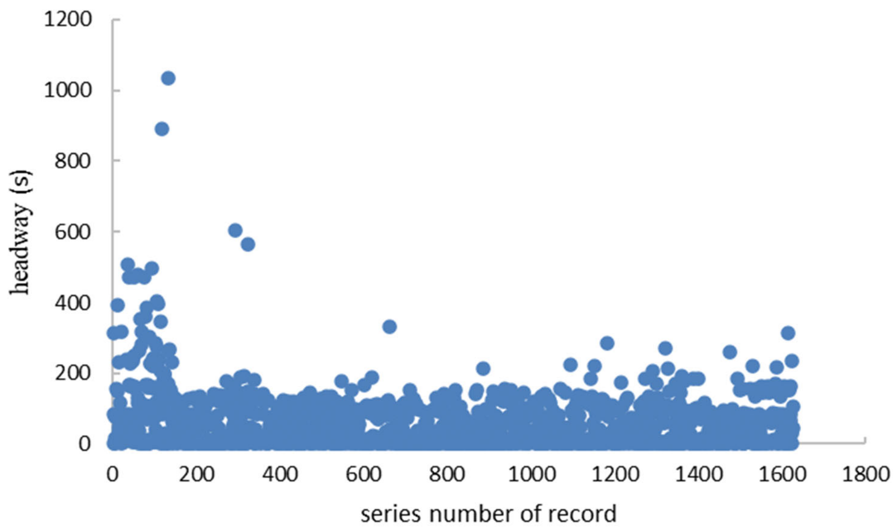
Using the data from December 2nd as an example, based on the length of the road section and the speed limit rules, the raw data set was cleaned to remove redundant and abnormal data, and a case data set suitable for analysis was obtained. The multivariate traffic parameter characteristics were presented within a typical road section, as shown in Figure 3, and the time-varying characteristics of headway, vehicle speed, and travel time were obtained.

4.2.1. Time-Varying Characteristics of Headway

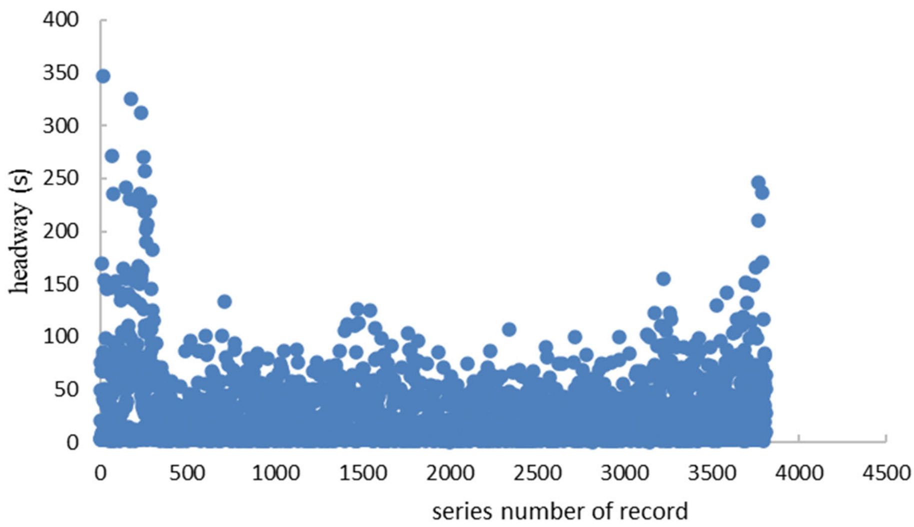
As shown in Figure 4, vehicles travel from detection point 6269 downstream, passing through detection point 6271 and exiting the road section at detection point 6273. The main traffic flow within the analysis object enters from detection point 6269. Therefore, in this section, we analyze the headway characteristics of each lane at the position of detection point 6269. The headway scatters are shown in Figure 5, where the y axis is the headway and the x axis is the series number of records.

An analysis of Figure 5 reveals that the total number of valid records for the three lanes of Section 6269 exceeded that of 6800. The number of vehicles passing through Lane 2 exceeded that of Lane 1 and Lane 3, indicating that the main driving requirement was concentrated in Lane 2, i.e., the middle lane, which aligns with actual driving habits. This is because the lanes at the entrance and exit are easily impacted by intersections, so most drivers choose to drive in the middle lane.

Regarding the distribution characteristics of headway, some abnormal values are exhibited in each lane; these values appeared during the early morning hours when vehicle movement was relatively low. The large headway between vehicles passing through the section is consistent with the actual conditions. For other periods, the headway is mainly distributed within 200 s. Due to the influence of the signal intersection cycle time, the generated headway time series also exhibits obvious periodic variation characteristics. However, due to the traffic density changes and the impact of vehicles arriving at adjacent intersections, the headway of vehicles passing through each cycle also exhibits complex variation patterns.

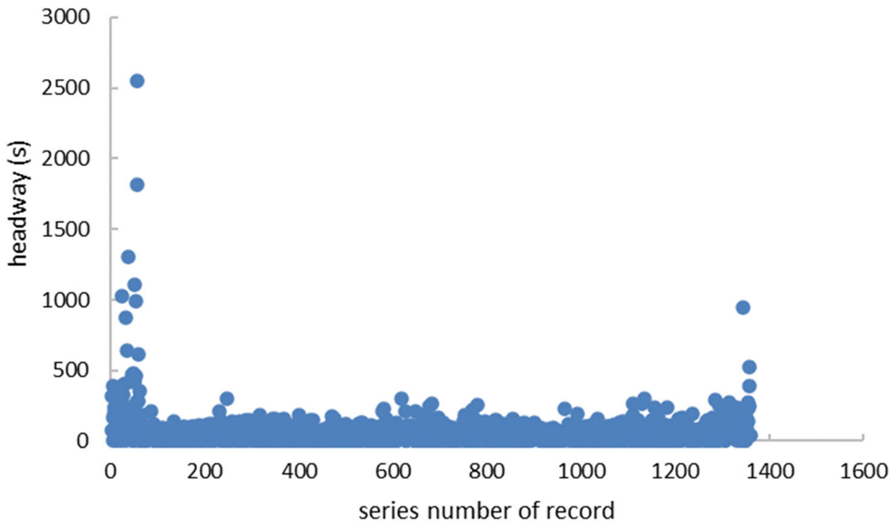


(**a**)



(**b**)

Figure 5. *Cont.*



(c)

Figure 5. (**a**) Headway scatter for lane 1 at detection point 6269. (**b**) Headway scatter for lane 2 at detection point 6269. (**c**) Headway scatter for lane 3 at detection point 6269.

4.2.2. Time-Varying Characteristics of Vehicle Speed

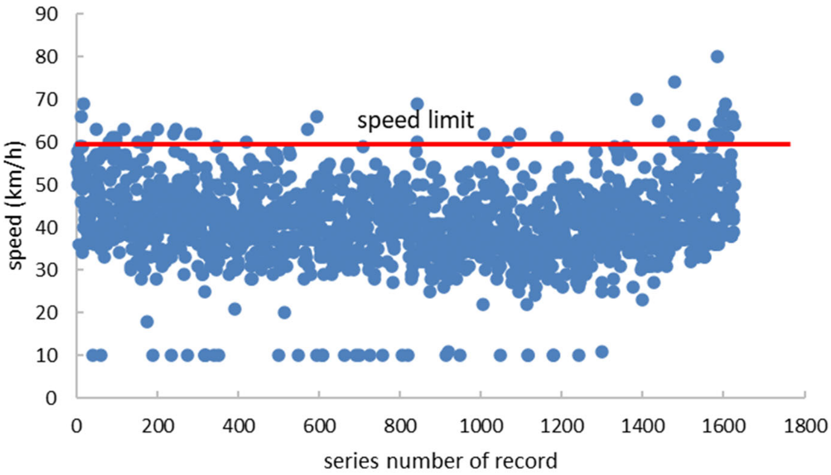
In this section, we show the vehicle speed distribution in the three detection sections, with the vehicles entering from lane 1 as the main analysis object. The speed of these vehicles passing through the downstream two sections was identified, and the distribution of vehicle speed scatter points was plotted as shown in Figure 6, where the y axis is the speed and the x axis is the speed series number of records; the speed limit is 60 km/h shown as the red line in Figure 6.

Regarding the speed sequences detected at the three sections, some of the sections have speed values that exceed or approach the speed limit, as shown in Figure 6. This is due to the low vehicle density and good traffic conditions during the corresponding period, where several vehicles accelerate and leave at higher speeds, resulting in higher speed data. Additionally, several outliers exist that may be caused by equipment malfunctions during data collection. For the remaining data, the headway is mainly distributed between 10 and 60 km/h, and the speed significantly fluctuates, exhibiting complex variation characteristics.

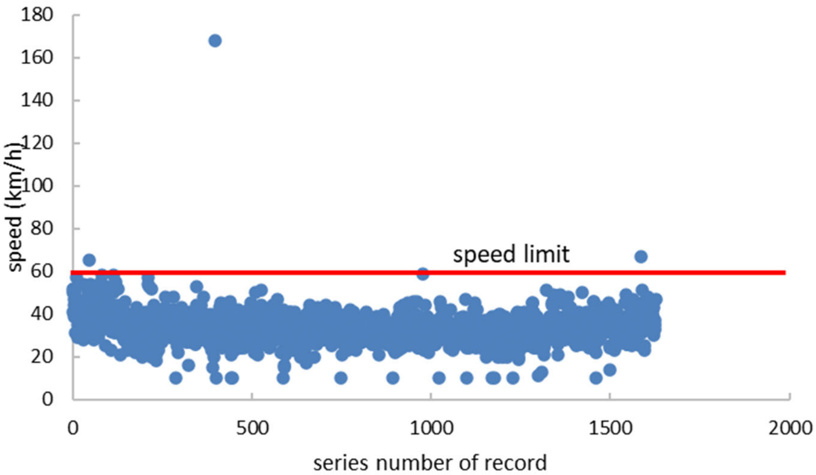
4.2.3. Time-Varying Characteristics of Travel Time

As shown in Figure 3, vehicles traveled between consecutive detection sections and generated multiple travel time sequences. In this example, the time between detection sections 6269 and 6271, the time between detection sections 6271 and 6273, and the time between detection sections 6269 and 6273 are used as examples to display the trip time scatter plot, where the x axis is the travel time and the y axis is the series number of travel time records.

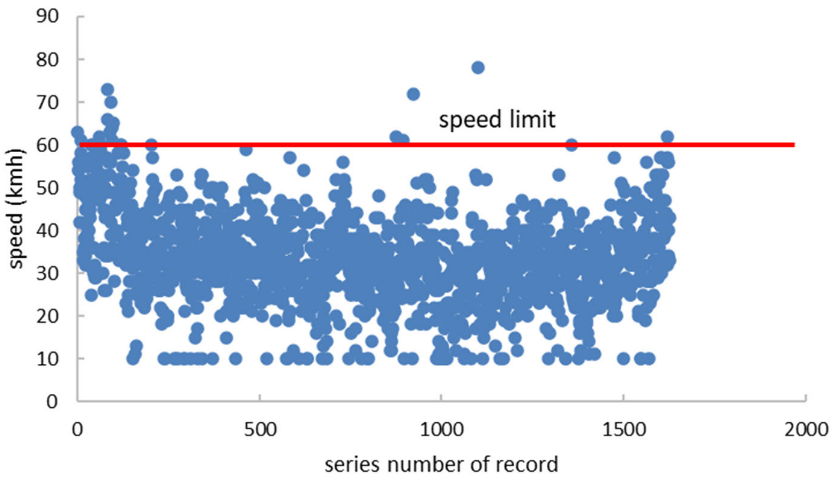
As shown in Figure 7, the travel times between adjacent detection sections exhibit different variation characteristics. The travel time between two adjacent upstream sections is influenced by the signal control cycle of the intersection and includes red light waiting and queuing times. This characteristic is more obvious in the downstream adjacent sections and follows a layered distribution. The travel time distribution from the starting point detection section to the end point detection section shows a complex increasing and decreasing trend.



(**a**)

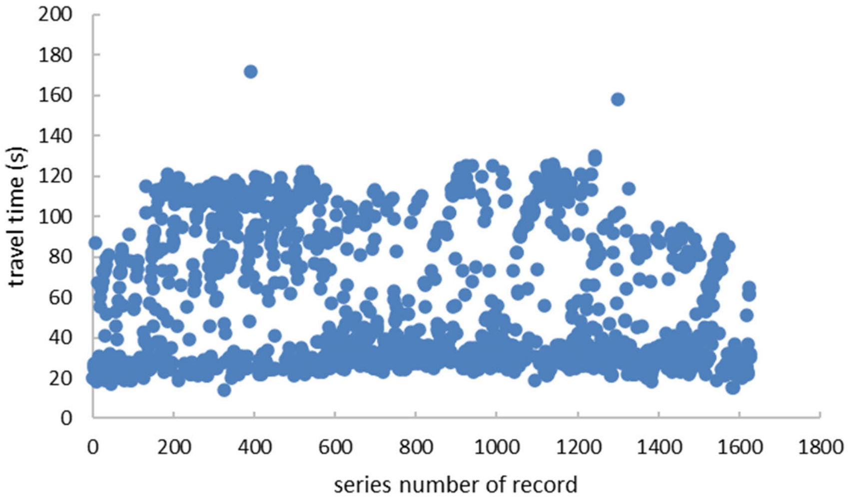


(**b**)

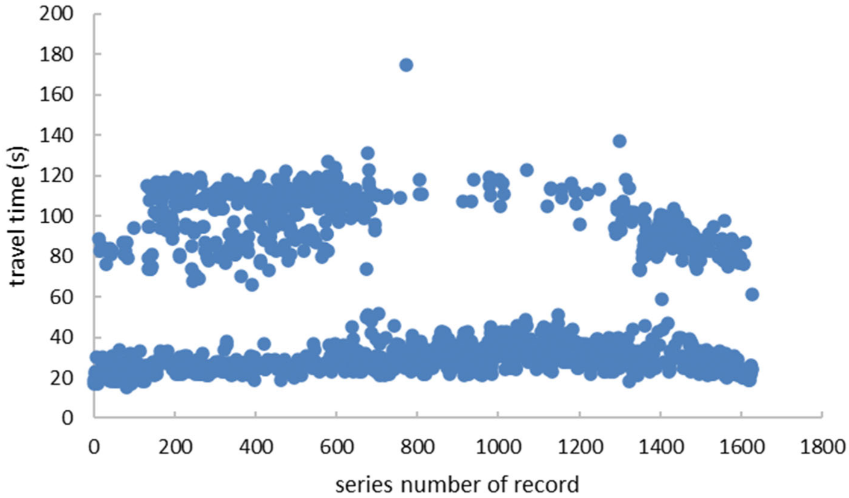


(**c**)

Figure 6. (**a**) Speed scatter for lane 1 at detection location 6269. (**b**) Speed scatter at detection location 6271. (**c**) Speed scatter at detection location 6273.



(**a**)



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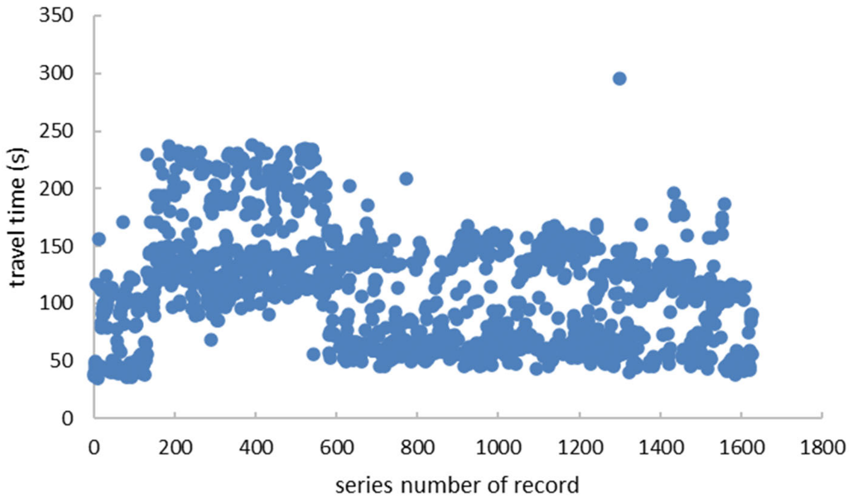


(**c**)

Figure 7. (**a**) Travel time scatter from 6269 to 6271. (**b**) Travel time scatter from 6271 to 6273. (**c**) Travel time scatter from 6269 to 6273.

4.2.4. Multivariate Traffic Parameter Phase Space Reconstruction

An analysis of the time series characteristics of multivariate traffic parameters reveals that they exhibit relatively complex variation patterns. To quantify their complex features, we selected three typical sections from Figure 4 and conducted a multivariate phase space reconstruction using the time series data of vehicle speeds, headways in Section 1, first section travel times, and total travel times. Based on 500 time series records collected from the sections, the MATLAB ChaosToolbox_lzb3.0 toolbox was used to calculate the embedding dimension and time delay results of the multivariate parameters [46,47]. The results indicate that each element variable in the multivariate phase space exhibits chaotic characteristics. These results are shown in Table 4.

Table 4. Multivariate variable phase space reconstruction with an embedding dimension and a time delay.

	Speed at Section 1 Lane 1	Headway	Speed at Section 2	Speed at Section 3	Travel Time for Section 1	Travel Time
Embedding Dimension, m	22	20	9	44	3	25
Time Delay	1	1	1	1	2	1
Largest Lyapunov index	0.002	0.003	0.001	0.004	0.002	0.002

In addition, based on the embedding dimension and time delay calculation results of each traffic parameter in Table 5, for example, a 500 × 6 matrix can be reconstructed as a 457 × 123 phase space.

Table 5. Structure of the long short-term neural network.

	Name	Type	Activations
1	Sequence input Sequence input with 52 dimensions	Sequence Input	52
2	lSTM LSTM with 200 hidden units	LSTM	200
3	Dropout 20% dropout	Dropout	200
4	relu Relu	ReLU	200
5	fc One fully connected layer	Fully Connected	1
6	Regression output Mean squared error with response 'Response'	Regression Output	-

4.3. Parameter Prediction and State Analysis

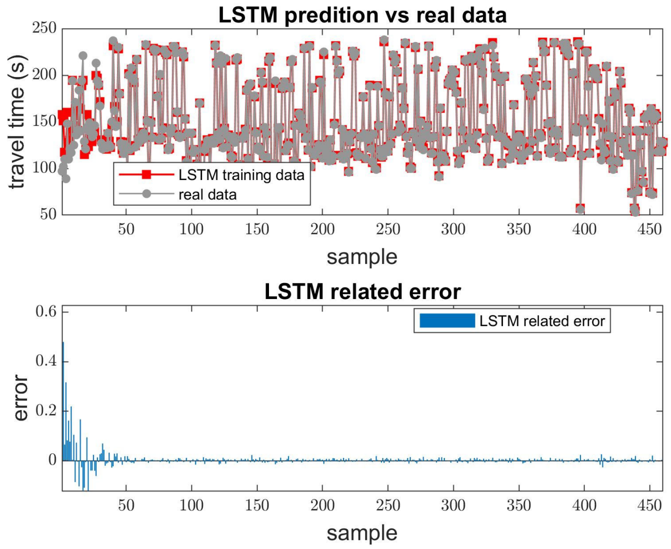
In this section, we predict the parameters after the multivariate traffic parameter phase space reconstruction. Based on the predicted results, we calculate the spatiotemporal state value of the road traffic in the example section using Formula (12).

LSTM is utilized to construct the evolution of phase space phase points and predict multivariate traffic parameters [48]. We referred to the LSTM network structure design parameter rules in MATLAB R2020a, and we set the input size to 52 combined with the feature dimensions after multi-parameter phase space reconstruction. We set the fully connected layers to 1, and we set the hidden layers to 200 and the dropout rate to 0.2 with a RELU activation function after multiple rounds of numerical experiments. The results meet the prediction accuracy requirements. The deep learning network structure is depicted in Table 5.

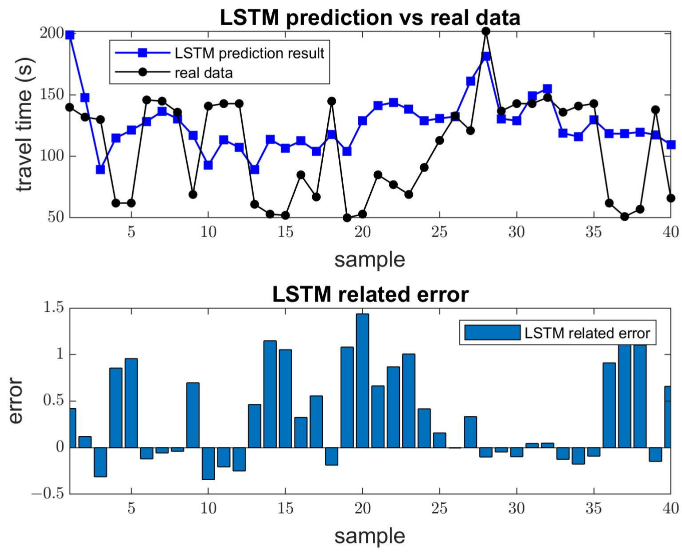
4.3.1. Training and Prediction

(1) Training and prediction of traffic parameters based on the LSTM method.

In this section, we first select the LSTM method to predict the multivariate traffic parameters. The time series of the six parameters shown in Table 4 was studied, where the vehicle speed, headway, and upstream travel time were selected as independent variables for the prediction model, and the total travel time was taken as the dependent variable. Using the learning and predicting ability of LSTM, the model was trained using the first 460 time slices as the training set and the last 40 time slices as the testing set, with 0.990 (MAE), 0.007 (MAPE), and 2.971 (RMSE). The training fitting and prediction results of the multivariate traffic parameters were obtained as shown in Figure 8.



(**a**)

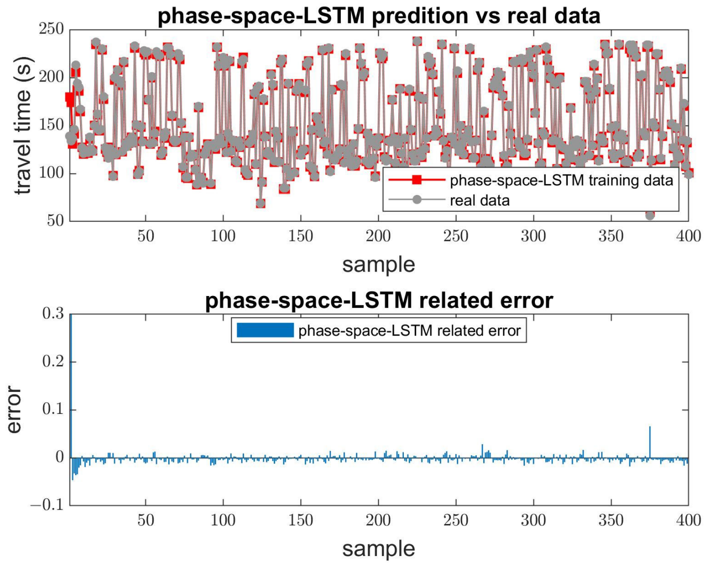


(**b**)

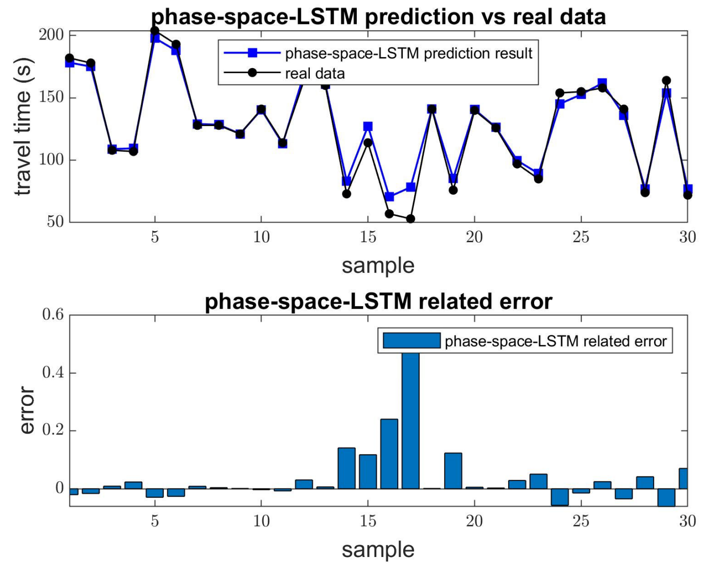
Figure 8. (**a**). Training results from LSTM for travel time parameters. (**b**) Prediction results from LSTM for travel time parameters.

(2) Training and prediction of traffic parameters based on the LSTM method with phase space reconstruction.

In this section, phase space reconstruction technology is combined with the LSTM method to predict multivariate traffic parameters. For the time series of six parameters, the vehicle speed, headway, and upstream travel time were selected as independent variables for the prediction model, and the total travel time was taken as the dependent variable. Using the learning and predicting ability of LSTM, the reconstructed multivariate variable time slices were used as the training set, and the last 40 time slices were used as the testing set, with 3.806 (MAE), 0.043 (MAPE), and 5.386 (RMSE). The training fitting and prediction results of the reconstructed multivariate traffic variables were obtained as shown in Figure 9.



(a)

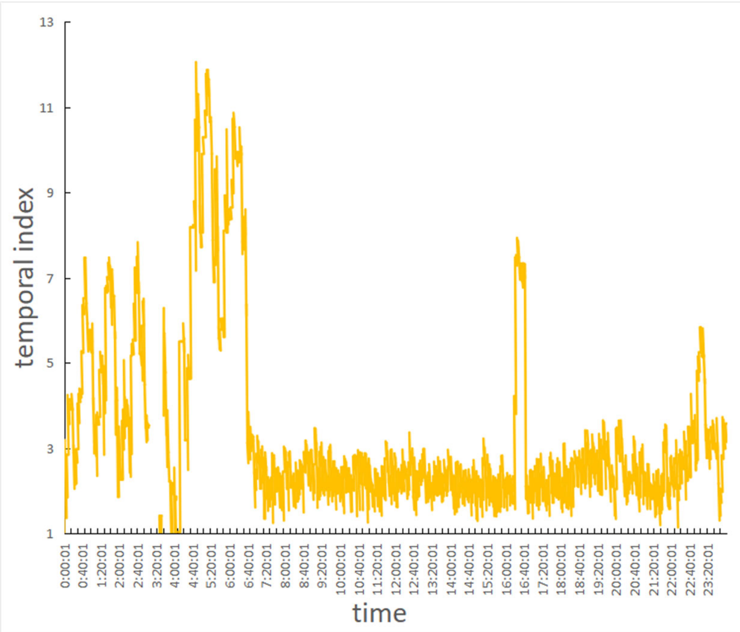


(b)

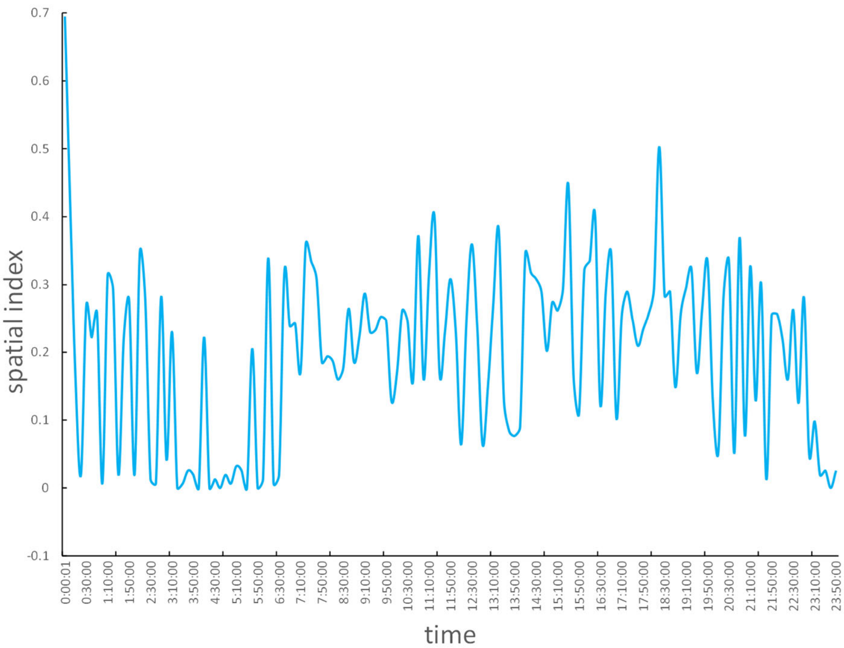
Figure 9. (**a**) Training results from LSTM with phase space reconstruction for travel time parameters. (**b**) Prediction results from LSTM with phase space reconstruction for travel time parameters.

4.3.2. Traffic Spatiotemporal State Parameter Calculation Based on Prediction

With the help of phase space LSTM predictions of traffic parameters, including the travel time, speed, and headway, we could predict the TP via Formula (12) with weight coefficients α and β. Based on the prediction results and using Formula (12), the travel-time-related state parameters and spatial state parameters, such as the queue length, for each lane in the case road section could be calculated. Selecting a suitable weight coefficient of 0.25 allows the weighted traffic spatiotemporal state parameters to be obtained. These results are shown in Figure 10.

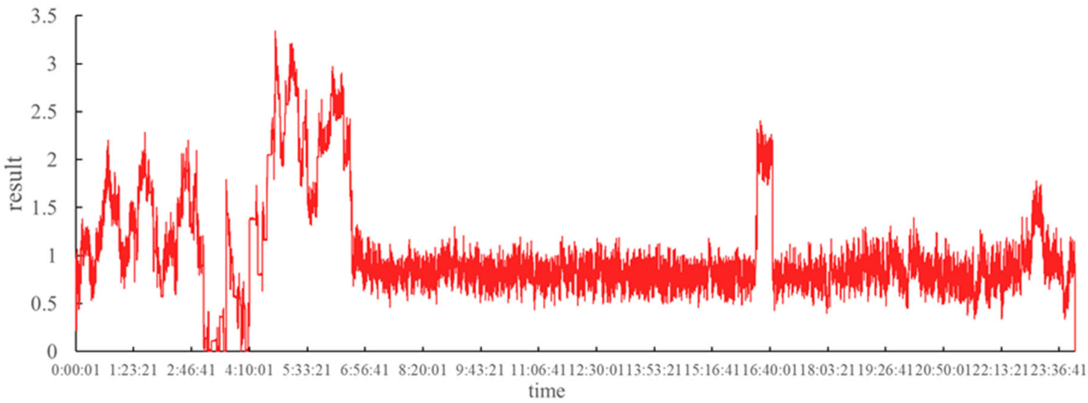


(**a**)



(**b**)

Figure 10. *Cont.*



(**c**)

Figure 10. (**a**) The results for travel-time-related state parameters. (**b**) The results for spatial state parameters. (**c**) The results for traffic spatiotemporal state parameters.

5. Conclusions

The current urban road traffic operational status assessment criteria focus primarily on the road sections between upstream and downstream detectors, using the vehicle travel time as the main evaluation index obtained within a certain time interval. Although this approach is simple and straightforward, it neglects the uneven distribution of vehicles arriving at adjacent road sections due to the periodic conversion of traffic rules at intersections. In this paper, we defined the traffic spatiotemporal parameters considering travel time, speed, and queuing situation by selecting traffic parameters from the time and space dimensions, and the phase space of multivariate traffic parameters was reconstructed using the single variable phase space. The chaotic characteristics were also analyzed. Next, we applied an LSTM model considering multivariate traffic parameters to predict traffic variables, and traffic parameters were predicted and traffic spatiotemporal parameters with were analyzed using RFID data in practical examples. By a results comparison, we found that the parameter prediction precision was better than the basic LSTM model. The main contributions of this article are as follows.

First, we selected lane-level detection parameters, interpreted the meaning of the road traffic spatiotemporal state from the two dimensions of time and space, and devised a traffic spatiotemporal state calculation method that considers multiple traffic parameters.

Second, we constructed a phase space of multivariate traffic parameters based on the nonlinear characteristics of the time series of multiple traffic parameters, integrated the LSTM prediction model, and constructed a phase space reconstruction LSTM prediction model that achieved a significantly improved accuracy.

Third, we used real urban road data to predict the changing characteristics of multivariate traffic parameters and calculated the road traffic spatiotemporal state based on the predicted results, which can provide a theoretical basis and practical reference for road traffic state evaluations.

In this paper, we analyzed the spatiotemporal evolution of traffic state parameters using RFID data and obtained prediction results. These results were derived from objective conditions. However, for urban traffic, using a large amount of sensory data to design a more reasonable traffic control strategy is an effective method to change the traffic operational status, which is also our future research direction.

Author Contributions: J.G., B.Z. and H.K. were responsible for research conception and design. J.G., N.W., S.H. and S.L. were responsible for data processing and analysis. J.G., B.Z. and H.K. were responsible for the analysis and discussion of results. N.W. and J.G. were responsible for draft manuscript writing and language. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

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