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Research Article

BP Neural Network-Based Big Data Intelligent Travel Algorithm and Its Application

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With the increase of urbanization rate, a large number of people flood into cities, increasing pressure of urban traffic, and problems accumulated in the taxi industry are gradually prominent. The phenomenon of crowded queue for taxi is frequent in peak hours, and vehicles patrol and sweep streets during peak hours. The key to solve these problems lies in mastering the rules and patterns of taxi travel and finding the factors affecting the relationship between taxi supply and demand. It is difficult to effectively understand taxi travel as a whole due to the large number of taxis and their large scale and strong mobility. Comprehensive application of trajectory data mining method can extract the spatiotemporal characteristics of massive taxi trajectory data and reveal the nature of its occurrence. This paper mainly focuses on the problems faced by urban traffic governance, such as the mismatch between data sources and demand systems, the uncoordinated operation of comprehensive transportation system, and the difficulty in sharing big data resources between government and enterprises. With massive data resources across departments, this paper designed a networked intelligent computing platform for big data of urban transportation integrated with various modes of transportation to sense the operation situation of urban comprehensive transportation system in real time, accurately grasp the space-time distribution of urban transportation supply and demand, and significantly improve the ability of coordinated operation, organization, and management of transportation in large cities. It also effectively enhances the quality of transportation information sharing and integration services and comprehensively improves the efficiency and overall carrying capacity of the urban comprehensive transportation system.

1. Introduction

Modern urban comprehensive transportation is an important carrier to support the normal operation of a city and guarantee residents' life [1]. Data integration mechanism for urban traffic management in our country and innovative applications platform as a whole are still in the primary stage of data integration, facing the construction unit partition, system, information island, fragmentation data management, artificial intelligence, and low level of big data applications challenge that cannot meet the urban traffic system management efficiently and orderly, wisdom resource scientific configuration. The need for data openness and integration. Based on time and space distribution of taxi data research, most can reflect the transportation personnel in the city of dynamic distribution of geographical space for the dynamic space-time distribution directly reflects the population, employment, travel, road and living space and a series of with the spatial layout of land use governance is directly related to spatial planning such as influencing factors [2, 3].

Through the acquisition, analysis, and fusion of urban traffic big data, as well as the analysis and prediction of operation state, the effective monitoring and management of urban traffic can be realized, the capacity and service level of the whole road network can be improved, and a refined data set for modern urban traffic governance can be formed. At present, the city space layout research mostly focus on the seeking of the static relationship between urban spatial elements, such as traffic network population and land use, ignoring the study of urban spatial dynamic indexes such as active degree, and dynamic index such as urban space activity can intuitively reflect the aggregation degree of city space quickly [4]. It is of great significance to analyze and guide the distribution of urban economic and social land and transportation, especially for the layout and optimization of urban commercial land. In the past, there have been abundant researches on indicators of urban spatial activity degree, and the research on acquisition methods of urban Hot Spots and other similar indicators is also relatively mature. Based on previous studies, it can be seen that traffic travel is an important cause of urban space activity. Therefore, this paper assumes that the active area of traffic can reflect the active degree of urban space in this region, that is, the active area of urban space. Through big data analysis of smart travel, active urban space is found, and its spatial correlation with urban commercial land is verified through correlation analysis, so as to guide the evaluation of urban commercial land [5–8].

Since the twenty-first century, with the method of cloud platform, based on the cloud computing architectures high compatibility, set up the urban traffic data intelligent computing cloud platform, through the integration of data mining, deep learning, edge, heterogeneous computing technology, such as building for refinement, intelligent, real-time traffic monitoring scheduling, and operation management of urban intelligent traffic management paradigm [9]. Traffic congestion governance is a governance problem faced by all cities in the world. Comprehensive, objective, accurate, and timely grasp of city-level large-scale traffic operation rules is of vital significance to traffic congestion governance. Used in traffic data-driven governance mainly face the following four aspects of the problem: one is the cognitive modeling ability is insufficient, the existing traffic data collection facilities generally single function isolated deployment, multisource heterogeneous data in time and space fragmentation distribution, and the lack of data correlation analysis. The second is that the reasoning ability is insufficient, and the traffic situation analysis focuses on the traffic flow. It is urgent to systematically sort out and apply the knowledge and experience of traffic governance [10]. Third, the capacity of large-scale computing is insufficient, and the elastic expansion capacity and large-scale instantaneous computing capability of the existing centralized computing platform of urban traffic are facing challenges. Fourth, the practical ability of governance is insufficient. Cities at different stages of transport development face different governance problems and scenarios and lack professional and effective platform and tool support, so as to enable multiparty cooperation to comprehensively improve the operation efficiency and service level of transport system [12, 13].

In terms of the intelligent governance of urban traffic, major cities in China have initially established various traffic big data collection systems. Developing the evaluation system. But how to effectively integrate the various types of data, forming a powerful traffic computing platform, to control traffic real-time running state to state for a long time, is the key to the city, city transportation management at home and abroad in the video image structured processing multisource data fusion traffic data modeling chart database system state nowcasting cloud computing traffic management carried out in such aspects as the related research and application of exploration. But scene data sensing technology based on the traffic control is not yet mature, cross-media multisource heterogeneous traffic data of data fusion and knowledge mining technology bottleneck, urban transport complex adaptive system both short-term and long-term mechanisms of cognitive are not clear, there is no intelligent computing platform for urban complex transportation system governance. The data accumulated in the process of traffic operation have the characteristics of multitypes, multisources, and heterogeneity [14]. The data provided by different information sources are all in their own reference frame, resulting in the disunity of the spatiotemporal datum and scale of multisource and heterogeneous traffic big data and the incomplete image view in the spatial coverage area of traffic big data. Based on the algorithm of feature representation feature fusion and multistage segment fusion of multisource heterogeneous traffic big data, the multidimensional fusion of traffic big data from different sources and granularity is carried out by combining the self-encoder transfer learning, multitask learning, and multiview learning [15–17]. Based on the results of multisource heterogeneous fusion representation and analysis of traffic big data, heterogeneous fusion analysis applications such as individual behavior trajectory prediction, local traffic flow real-time estimation, overall traffic trend analysis, and OD time estimation are carried out from three aspects of coverage time granularity accuracy [18–25].

2. Related Works

In recent years, many experts and scholars at home and abroad have mined the spatial-temporal characteristics of taxi track data from different disciplinary perspectives and proposed many research methods, including descriptive statistics, density analysis, and cluster analysis. These methods can intuitively describe the overall distribution characteristics of data sets and are not limited by research assumptions and analysis models. They can be used as an independent method to mine trajectory data and can also be used for data preprocessing to provide basic support for subsequent research. Nesmachnow et al. [26] divided the study area of Lisbon into several grids, counted and visualized the trips in the grids, respectively, and represented the trips by the depth of color. Wang et al. [27] calculated the number of taxi arrivals within a certain range of service facilities such as restaurants and shopping based on taxi trajectory data, quantified the attractiveness level of various service facilities, and analyzed the spatial distribution pattern of the attractiveness through global and local spatial autocorrelation. Xiong et al. [28] extracted the pick-up and drop-off points from the taxi track data of Wuhan in a week and used the bar chart to show the daily taxi travel volume and the line chart to show the taxi travel volume in different periods of time. They counted the number of pick-up and drop-off points of Beijing in a month and calculated the working days and rest days. The average number of pick-up and drop-off points is visualized in the form of broken line graph to reveal the time series pattern of taxi trips in Beijing. Zheng et al. [29] studied the visualization of a large number of floating car data from the perspectives of global view and local view. The global view displays the distribution of regions selected by users in the form of focal graph, and the local view has 2D and 3D traffic parameter visualization symbols and numerous forms of charts.

Hou et al. [30] defined the external transport hub (airport railway station bus and passenger station) of Beijing as the research area and used the kernel density estimation method to compare and analyze the up-and-down passenger cluster area arriving at the transport hub and the disembarking passenger cluster area leaving the transport hub. Kibria et al. [31] taking Nanjing city as the research area, the bandwidth of kernel density estimation was determined by incremental spatial autocorrelation, and then the kernel density was used to detect the hot spots of taxi picking up and getting off, and the temporal and spatial law of taxi travel was analyzed. In order to effectively mine taxi trajectory data, Zhang [32] proposed a two-layer framework to automatically identify each taxi journey destination and estimate the return journey mode and destination using geographic points of interest data and taxi trajectory data, combined with three methods of spatiotemporal clustering Bayesian inference and Monte Carlo simulation. Massive information rich taxi trajectory data, using descriptive statistics method can understand the distribution of total body data, statistical travel frequency, travel distance trip length variables, such as, in turn, through a variety of straight view image visualization method to show the taxi travel mode, but has a certain generality, can accurately express travel fine feature kernel density analysis can extract regions with high point density, and the neighborhood size can affect the estimation results to a certain extent, which may lead to ring phenomenon. Chang [33] collected 222 traffic trips, with a total of nearly 580 000 GPS records, and each record includes speed, acceleration, and driving direction change characteristics. On this basis, the multilayer perceptron neural network, Bayesian network, and decision tree models are constructed, respectively, by using 75 quantiles of velocity, mean signal quality of deviation vector acceleration of velocity as the input of the model. The results show that the multilayer perceptron neural network and decision tree have good recognition accuracy.

Moreno et al. [34] used SVM model to identify travel modes, and the results showed that SVM had good application effect on travel mode recognition, but it did not optimize SVM parameters. As a result, although SVM model was adopted, the final identification accuracy was not high due to the nonoptimal combination of SVM parameters. Fonzone et al. [35] proposed a traffic mode identification method based on AGPS mobile phone. GPS data are collected by mobile phone software, such as instantaneous speed and acceleration, as the characteristics of traffic pattern recognition. The BP neural network (back propagation neural network, referred to as BP neural network) is used for traffic pattern recognition. Mohammadi and Al-Fuqaha [36] proposed transportation mode selection model based on neural network is established, to choose the gender, age, income, occupation, purpose of travel, the place of departure and arrival location, departure time, arrival time of the nine variables as the input of the model, the use of Xuzhou city, Jiangsu province transport in the large-scale urban population trip survey sampling investigation as an example, the measured data Identify walking, cycling and bus travel patterns. But the study identified a lack of taxis, subways and other modes of transportation, which are an important part of transportation.

From the above analysis, we know that the above methods have studied the big data intelligent travel to some extent. However, some problem still exists. For example, no scholar has applied the BP neural networks to this field till now, so the research here is still a blank, which has great theoretical research and practical application value for optimal management of financial assets.

This paper consists of five parts. Section 1 and Section 2 give the research status and background. Section 3 is BP neural network-based big data intelligent travel algorithm. Section 4 shows the experimental results and analysis. The experimental results of this paper are introduced and compared and analyzed with relevant comparison algorithms followed. Finally, Section 5 concludes the full paper.

3. BP Neural Network-Based Big Data Intelligent Travel

3.1. BP Neural Network. Backpropagation neural network (BP neural network) is a supervised learning algorithm, which is often used to train multilayer perceptron because BP neural network successfully solves the problem. In order to solve the weight adjustment problem of multilayer feedforward neural network of nonlinear continuous function, nearly 90% of neural network models in the real application of artificial neural network are BP neural network and its variation form. BP network has a structure of three or more layers, namely input layer, one or more layers of hide layer, and output layer. The neurons between each layer are fully connected, and all neurons in the layer are not connected. The nodes of each hidden layer are generally used. The brief structure of Sigmoid excitation function BP neural network is shown in Figure 1, where the threshold value is not drawn. The number of the nodes of the hidden layer is fix in this paper, and also the number of the output layer.

There are n neurons in the input layer. The input vector is

$$X = (x_1, x_2, \cdots, x_n)^T \tag{1}$$

The hidden layer has L spirit meridian elements, the output layer has M neurons, and the output vector is

$$Y = (y_1, y_2, \cdots, y_m)^T \tag{2}$$

Before the prediction of BP neural network, network training should be carried out first. By network training, the weight threshold can be adjusted to make the network have associative memory and prediction ability. The training process of BP network includes the following steps:

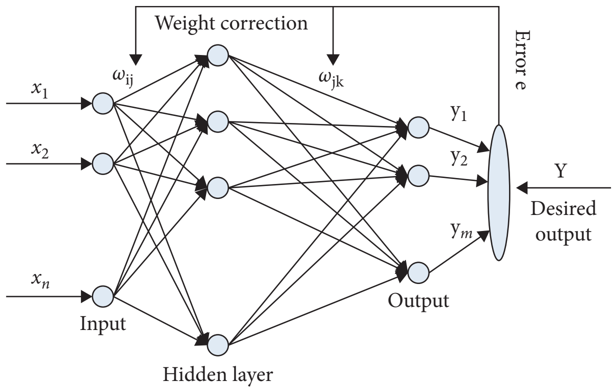


Figure 1: Flow chart of PSO algorithm.

The hidden layer output is calculated according to the input vector X, the connection weights between the input layer and the hidden layer I and J, and the hidden layer threshold, compute the hidden layer output H:

$$H_j = f\left(\sum_{i=1}^{n} \omega_{ij} x_i - a_j\right), j = 1, 2, \cdots, l. \tag{3}$$

Here, L is the number of nodes in the hidden layer and F is the excitation function of the hidden layer:

$$s.t. \sum_{i=1}^{n} w_i u_i = r, \sum_{i=1}^{n} w_i = 1. \tag{4}$$

The output calculation of the output layer is based on the output H of the hidden layer, and the connection weight between the hidden layer and the output layer is J k and the threshold of each neuron of the output layer:

$$\begin{aligned} &\text{Max} \sum_{i=1}^{n} w_i u_i \\ &O_k = \sum_{j=1}^{l} H_j \omega_{jk} - b_k, \quad k = 1, 2, \ldots, m. \end{aligned} \tag{5}$$

The network prediction error is calculated according to the network predicted output O and expected output Y:

$$e_k = Y_k - O_k, k = 1, 2, \cdots, m. \tag{6}$$

Network connection weights are updated according to network prediction error:

$$\begin{aligned} &\omega_{ij} = \omega_{ij} + \eta H_j \left(1 - H_j\right) x_i \sum_{k=1}^{m} \omega_{jk} e_k, \quad i = 1, 2, \ldots, n; j = 1, 2, \ldots, l, \\ &\omega_{jk} = \omega_{jk} + \eta H_j e_k, \quad j = 1, 2, \ldots, l; k = 1, 2, \ldots, m. \end{aligned} \tag{7}$$

Update the network node threshold according to network prediction error:

$$\begin{aligned} &a_j = a_j + \eta H_j \left(1 - H_j\right) \sum_{k=1}^{m} \omega_{jk} e_k, \quad j = 1, 2, \ldots, l, \\ &b_k = b_k + e_k, \quad k = 1, 2, \ldots, m. \end{aligned} \tag{8}$$

Determine whether the algorithm iteration is finished, if not:

$$E\left(r_k\right) = r_f + \beta\left(E\left(r_M\right) - r_f\right). \tag{9}$$

3.2. Particle Swarm Optimization. The research puts forward a multiauxiliary information fusion space-time model, which can better deal with the dynamic and complexity of traffic flow (Figure 2). Second, it breaks through the traffic knowledge mining technology based on reasoning of temporal knowledge association rules and realizes the completion of incomplete knowledge base and mining of tacit knowledge by using spatiotemporal matching and periodic rules.

Aiming at the problem that the efficiency of association retrieval of complex rules of mass knowledge is low due to the high requirement of effectiveness in traffic governance scenes, the knowledge efficient retrieval technology based on graph database is firstly broken through, and the community attribute search algorithm is used to realize the rapid retrieval of mass data and multidimensional complex association relations. Secondly, it breaks through the traffic knowledge mining technology in typical governance scenarios, and develops knowledge mining models of 7 individual activity travel rules, people affected by traffic events, and travel characteristics of large-scale activities, so as to realize in-depth mining and knowledge retrieval of complex rules in typical governance scenarios.

The overall process of constructing the influencing factor model of taxi travel is shown in Figure 3. First, a variety of tools such as fishing nets and grid calculator model builder are created in ArcGIS Pro to quantify track points, road network, and POI data of population density, and the dependent variables of the model are obtained. Independent variables, OLS GWR MGWR regression model was constructed, respectively. During model construction, experimental parameters were repeatedly adjusted and model results were comprehensively compared for many times to obtain the optimal solution of each model.

4. Experimental Results and Analysis

4.1. Introduction to Experimental Environment and Data Set. In the overall process of constructing the influencing factor model of taxi travel, first, a variety of tools such as fishing nets

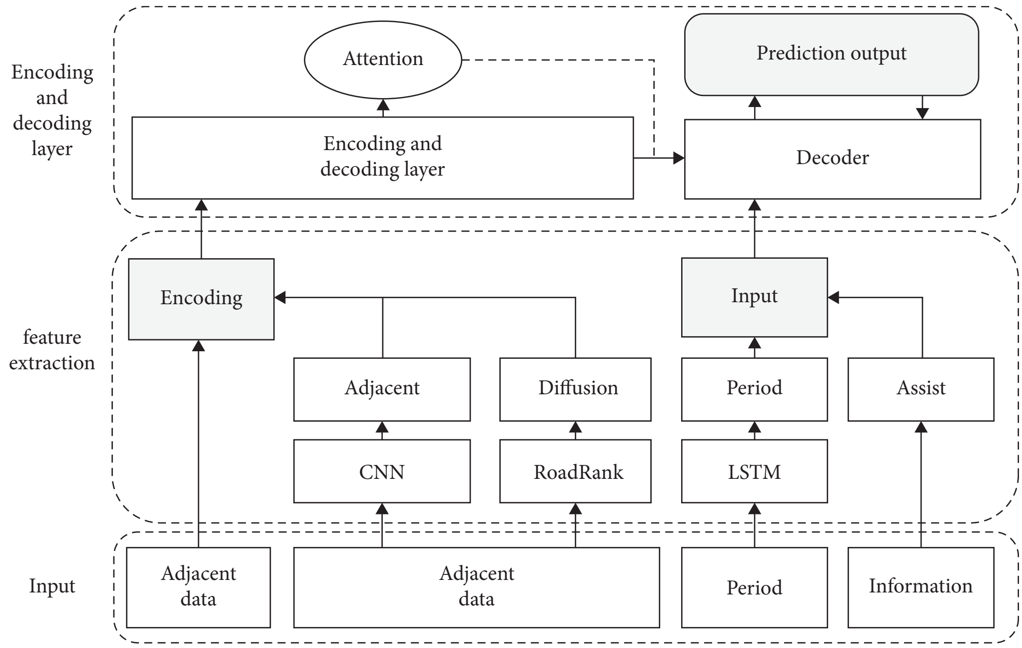


Figure 2: Multiauxiliary information fusion BP model considering traffic flow diffusion.

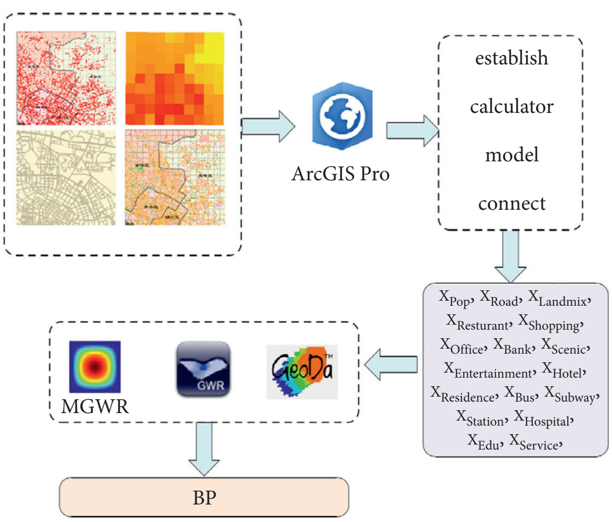


Figure 3: Comparison of optimization rate of three models.

and grid calculator model builder are created in ArcGIS Pro to quantify track points, road network, and POI data of population density, and the dependent variables of the model are obtained. For independent variables, OLS GWR MGWR regression model was constructed. During model construction, experimental parameters were repeatedly adjusted, and model results were comprehensively compared for many times to obtain the optimal solution of each model.

In this paper, the spatial data of Wuhan taxi provided by Sky Smart Travel Big data platform are used as the main data source, and other traditional statistics and related planning background data are used as auxiliary data for analysis and research.

4.2. Experimental Results Analysis. In order to verify the correlation of urban space active area and population distribution, the author extracted urban population density distribution and the urban space superposition found in the active region, and the urban space activity and has close relation with the city's population distribution, extracted the basic urban space active area that is located in the high-density urban core area, perfectly matching with the conventional judgment. It indicates that the urban spatial active area obtained by the above method is relatively accurate, as shown in Figure 4.

As shown in Figure 5, on a week-by-week basis, the highest number of trips were made on Friday, with about 3,000 fewer trips made on Saturday and the number of trips made on Sunday declined sharply, basically the lowest point or lower point in each cycle. On November 4, 11, 18, and 25, the four Fridays exceeded the usual number of trips. The time period when a large number of taxis took place at 18 : 00 in the evening is between 5 : 00 and 24 : 00, an average of 500 fewer trips per hour.

The law of arrival point is similar to that of the starting point, but the difference lies in the obvious fluctuation of arrival point, the peak value and valley value are more prominent, and the trend is not as smooth as that of the starting point. The peak time is relatively short, and 9 : 00, 13 : 00, and 18 : 00 constitute the peak of working days and 12 : 00 16 : 00 constitutes the low point. The low point of arrival on the rest day is at 16 : 00. Compared with the starting point, the trend change of arrival points and the increase of the number of arrival points have a certain backward delay, and the departure time is scattered and the arrival time is concentrated. In the morning of working days, the quantity of arrival points and starting points in the study

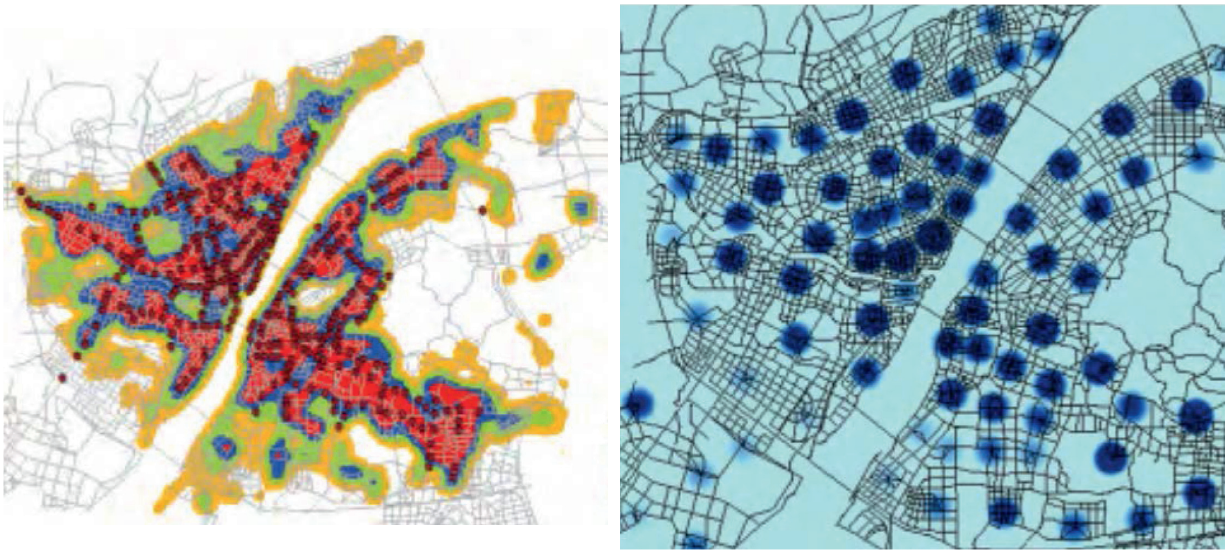


Figure 4: Matching map of population density and spatial active area.

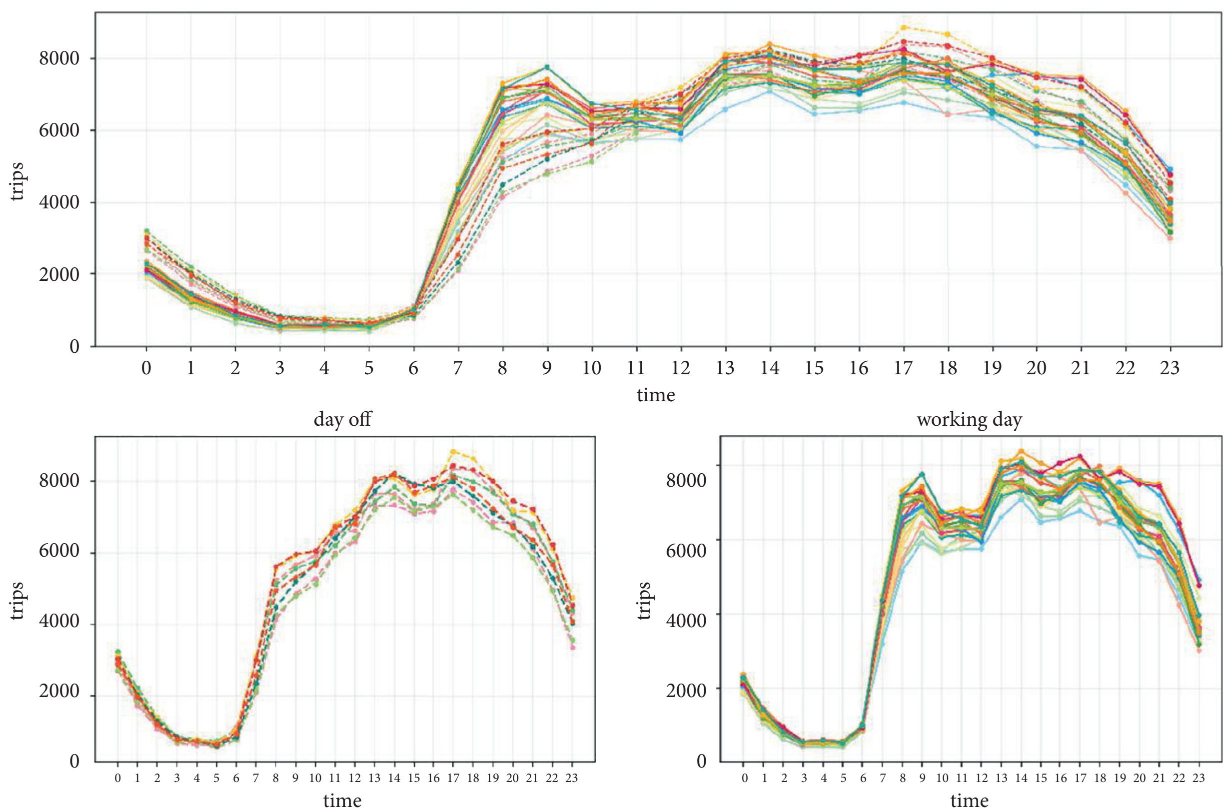


Figure 5: Distribution of arrivals on rest weekdays.

area differs greatly from 8 : 00 to 10 : 00, indicating that the regional inflow is greater than outflow in the morning.

The core points connected with density and the boundary points in the core point neighborhood together form a class. The red core points and yellow boundary points shown in Figure 6 belong to the same class, Density-Based Spatial Clustering of Applications with Noise (DBSCAN). The tightness of sample point distribution is measured by judging whether the sample points are connected in density. The closely connected samples are divided into one category to obtain a cluster category, and the samples connected in density are divided into different categories to obtain all cluster categories.

Advantages of hierarchical clustering: the definition of distance and similarity is simple, and there are few restrictions; there is no need to determine the number of classes before clustering; it can flexibly realize multilayer similarity clustering.

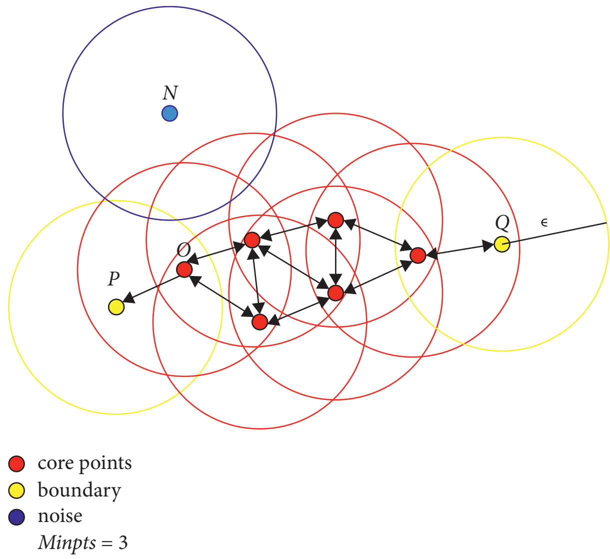


Figure 6: Cluster results of DBSCAN.

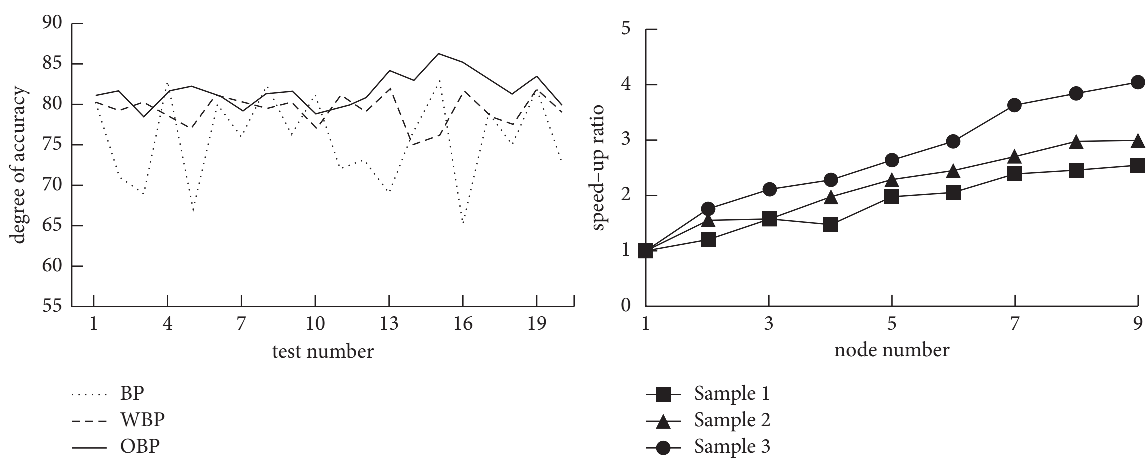
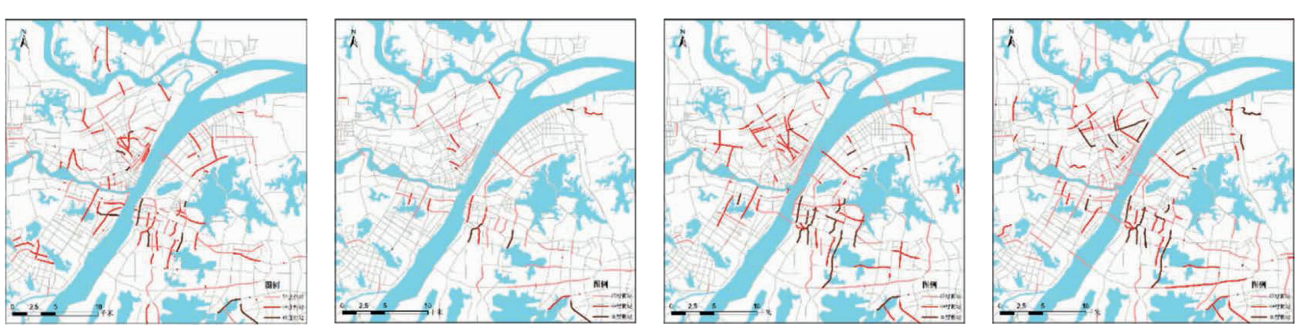


Figure 7: Comparison of accuracy and acceleration ratio test results.



(a) (b) (c) (d)

Figure 8: Sketch of global marginal ranking.

Disadvantages: distance matrix needs to be calculated, which has high time and space complexity. The extreme distribution of sample points affects the clustering accuracy. There may be chain-like clusters, and in the case of uneven distribution of data points and large difference in density, a single hierarchical threshold can only extract fixed cluster.

Automatic identification of travel modes with smart phone data can not only provide a large amount of data basis for traffic planning but also provide a basis for real-time

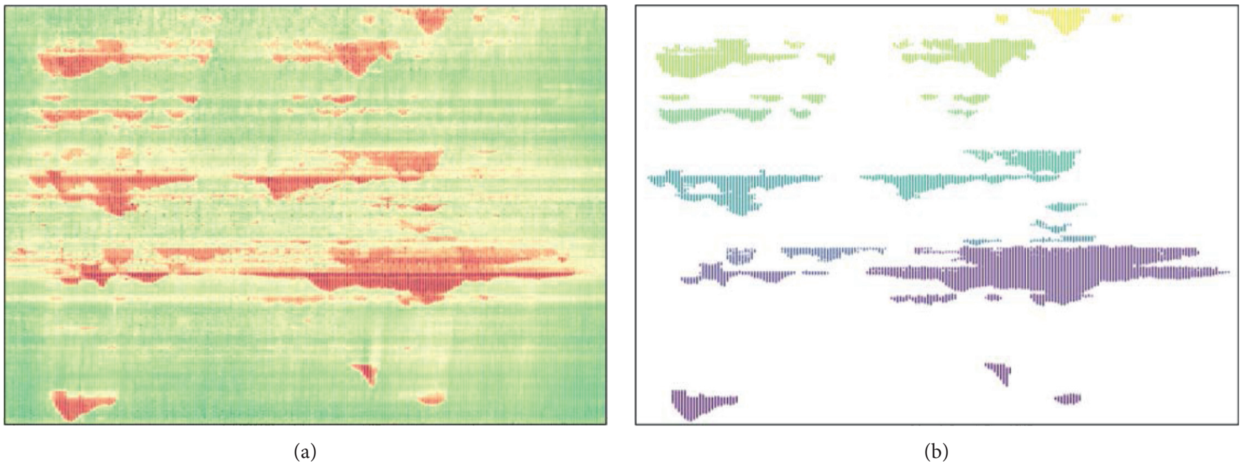


Figure 9: Travel congestion identification based on BP neural network.

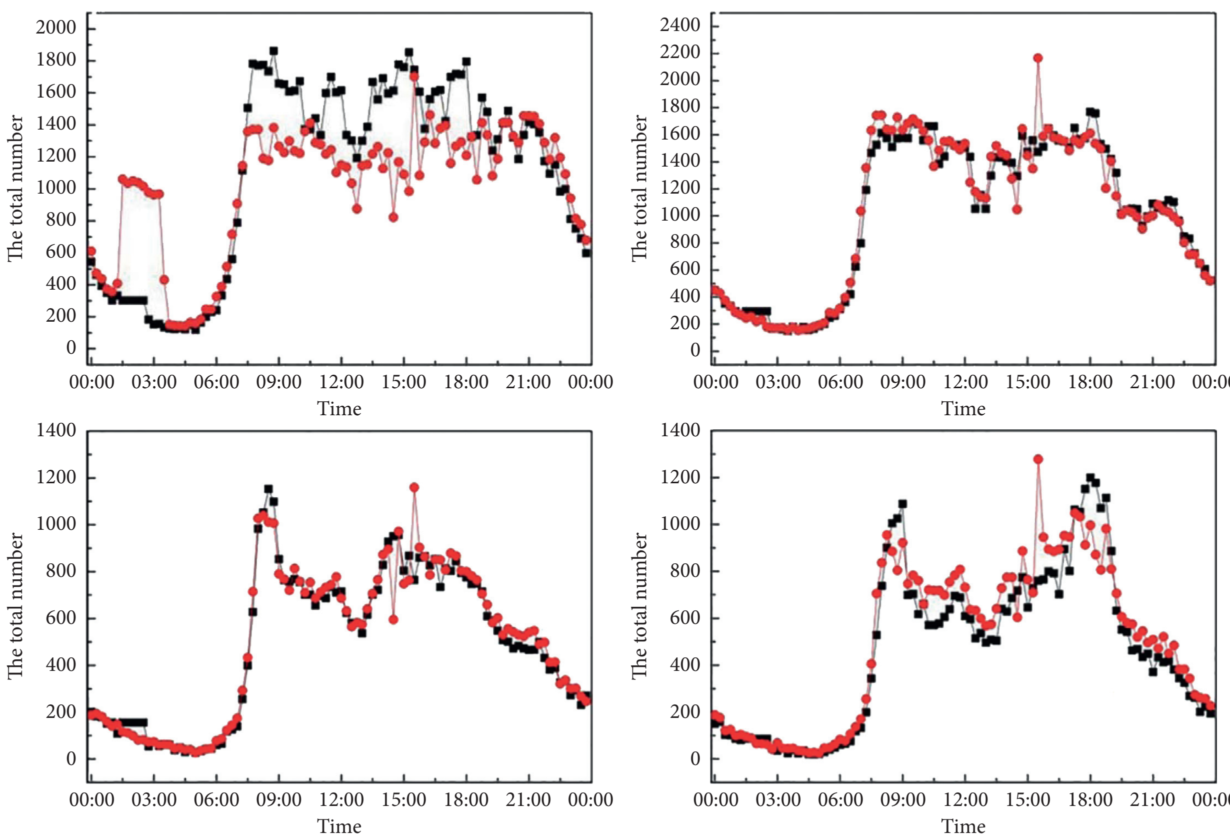


Figure 10: The prediction based on BP is compared with the measured data.

traffic control and guidance. However, traffic travel behavior itself is very complex, and travel background distance and other attributes are important factors affecting travel mode recognition. There is still a lot of work to be done in this direction in the future.

The number of nodes was successively increased to run the parallel FCM clustering integration algorithm, and the number of nodes was increased from 1 to 9. Data sample 1, sample 2, and sample 3 were clustered, respectively, and the time of each running was recorded. Each group of experiments was run for 10 times, respectively, and the average running situation was calculated, as shown in Figure 7. The acceleration ratio of all the three sample sizes shows an increasing trend, and the increasing trend is more obvious with the increase of the sample data volume, indicating that the algorithm has a strong ability to process large-scale data, and the acceleration ratio performance is good.

Cluster integration operation is carried out on 3 nodes, 6 nodes, and 9 nodes, respectively, for sample data of three sizes.

Record between the run time of each experiment, the experiment in each group is repeated 10 times, and the average operation is calculated, as shown in Figure 7. With the increase of the number of nodes, three samples of the algorithm running time are now to reduce the trend, the greater the amount of data, the decreasing trend, the more obvious can be seen from the diagram, sample 3 reduce the trend of the most obvious. The running time of the nine nodes is basically only one-third of that of the three nodes, while the other two samples are only reduced by about one half, so the algorithm has good scalability when processing large-scale data.

Before and after the epidemic, the morning rush hour congested roads on weekdays were visualized by levels, as shown in Figure 8. From the perspective of spatial distribution, the heavily congested roads before the epidemic (November 2019) mainly included Jiefang Avenue, Zhuyeshan interchange, Jiefang Road, Nanhu Road, Lhoshi Road, Fu Road, Guanggu Avenue, Yangguang Avenue, etc. In the initial stage of the resumption of work and production (March 2020), the distribution of congested sections was significantly reduced, including Baishazhou Avenue and Lhoshi Road and Auxiliary Road of Optics Valley Avenue. After the full resumption of work and production (June 2020), the urban traffic gradually recovered, and the traffic congestion gradually increased; After the recovery of the epidemic (August 2020), the number of severely congested roads increased significantly, mainly including Changqing Road, Zhuyeshan overpass, Sanyanqiao Road, Jiefang Road, Jiefang Road, Baishazhou Road, Zhongshan Road, and Luoshi Road, indicating that the urban traffic was further restored and the traffic pressure gradually increased.

Before and after the epidemic, the congested roads in the evening rush hours on weekdays were classified. Before the epidemic (November 2019), the heavily congested roads mainly included The Second Ring Road (Yangxin Road), Jiefang Road, Zhuye Mountain Interchange, Wuluo Road, Luoyu Road, Shengli Street, etc. In the early stage of the resumption of work and production (March 2020), the traffic congestion situation was significantly reduced, and all congested roads were significantly reduced. After the full resumption of work and production (June 2020), as in the morning rush hour, the congested sections increased significantly. The urban traffic gradually returned to normal, and the heavily congested sections mainly include Development Avenue, Jiefang Avenue, Sanyan Bridge Road, Joy Avenue, Jiefang Road, Bayi Road, Zhongbei Road, etc. On the one hand, it indicates that urban traffic has fully recovered, and on the other hand, traffic congestion has slightly intensified, which may be related to the increase in the proportion of self-driving trips after the recovery of the epidemic.

Aiming at the problem that it is difficult to accurately identify the influencing factors of traffic governance with multiple governance targets, the short-term congestion symptom recognition technology based on the trans-media traffic knowledge graph is broken through, and two symptom recognition models of road network congestion state and bus service level are constructed, with the success rate of congestion recognition reaching 92.4% (Figure 9). Based on the study of structural change points of bus passenger flow, the influence of track on bus is analyzed.

Aiming at the requirements of agile early warning of congestion in the whole urban road network, the technology method combining meso dynamic traffic simulation and deep learning was broken through. Taking Futian Central District of Shenzhen as the test object, the urban road network online deduced real traffic for 2 hours, and the test result of running time was 3.728 S, the prediction accuracy of key roads exceeds 85%, and the specific results are shown in Figure 10.

5. Conclusions

To sum up, this paper conducts theoretical and application research on the cognitive law of urban traffic complex system and the big data intelligent travel algorithm based on the BP neural network. The continued work has laid a solid foundation for the future to promote the integration of key technologies and more application demonstration scenarios and rely on the landing scenario to improve the data fusion perception traffic knowledge map traffic situation inference and cloud edge system platform indicators.

In terms of data fusion perception, it will rely on more application scenarios to further break through the theoretical and technical bottlenecks of traffic data processing and analysis, accurately extract and efficiently store effective information in traffic monitoring, and realize the restoration of the traffic panorama and in-depth analysis and cross analysis of its features.

Data Availability

The data set can be accessed upon request to the author.

Conflicts of Interest

The author declares no conflicts of interest.

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