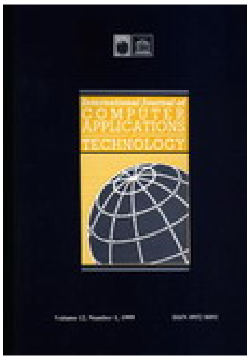


International Journal of Computer Applications in Technology

ISSN online: 1741-5047 - ISSN print: 0952-8091
https://www.inderscience.com/ijcat

Intelligent traffic congestion discrimination method based on wireless sensor network front-end data acquisition

Maokai Lai

DOI: 10.1504/IJCAT.2023.10059521

Article History:

Received:	04 April 2023
Last revised:	16 May 2023
Accepted:	31 July 2023
Published online:	03 October 2024

Intelligent traffic congestion discrimination method based on wireless sensor network front-end data acquisition

Maokai Lai

Chang'an Dublin International College of Transportation,
Chang'an University,
Xi'an, Shaanxi, China
Email: jubitlapras@163.com
*Corresponding author

Abstract: Conventional intelligent traffic congestion discrimination methods mainly use GPS terminals to collect traffic congestion data, which is vulnerable to the influence of vehicle time distribution, resulting in poor final discrimination effect. Necessary to design a new intelligent traffic congestion discrimination method based on wireless sensor network front-end data collection. That is to use the front-end data acquisition technology of wireless sensor network to generate a front-end data acquisition platform to obtain intelligent traffic congestion data, and then design an intelligent traffic congestion discrimination algorithm based on traffic congestion rules so as to achieve intelligent traffic congestion discrimination. The experimental results show that the intelligent traffic congestion discrimination method designed based on the front-end data collection of wireless sensor network has good discrimination effect, the obtained discrimination data is more accurate, effective and has certain application value, which has made certain contributions to reducing the frequency of urban traffic accidents.

Keywords: wireless sensor network; front-end; data acquisition; transportation; intelligence; traffic jam; distinguish; traffic congestion data.

Reference to this paper should be made as follows: Lai, M. (2024) 'Intelligent traffic congestion discrimination method based on wireless sensor network front-end data acquisition', *Int. J. Computer Applications in Technology*, Vol. 74, No. 3, pp.147–157.

Biographical notes: Maokai Lai is junior student from Chang'an Dublin International College of Transportation, Chang'an University, worked as an intern in 'Study on the connection strategy of highways and urban roads' in Jiangxi Province, China.

1 Introduction

With the growth of world population and economic development, the transportation routes of various countries are becoming more and more perfect and the types and number of transportation vehicles are increasing (Zeng et al., 2021). Research shows that the per capita vehicle occupancy rate is getting higher and higher, resulting in huge traffic pressure. Affected by urban infrastructure construction, most cities begin to suffer from traffic congestion (Pu and Luo, 2021), which leads to serious traffic accidents, not only affecting the normal life of urban residents, but also causing casualties, which is not conducive to the sustainable development of the city. In the past, traffic congestion was often identified and managed by human resources (Yadav and Rishi, 2021), but with the increase of the number of road vehicles, the efficiency of human management and regulation is becoming lower and lower, which cannot solve the growing urban traffic pressure. Therefore, an effective intelligent traffic congestion identification method (He et al., 2021) needs to be designed, there is an urgent need for Intelligent Transportation Systems (ITS) to alleviate traffic congestion and promote sustainable urban development. ITS includes various advanced technologies such as real-time traffic monitoring, traffic control, traffic prediction and management, intelligent vehicle systems and communication systems. Owing to the elements including road layout, traffic patterns, congestion levels and environmental conditions, the consequences of various strategies for discriminating between different types of traffic congestion might change depending on the type of road. To achieve precise discrimination and efficient traffic management, it is crucial to evaluate and adapt the strategies to individual road features. By integrating these technologies, ITS can improve the efficiency of traffic management and reduce traffic congestion, emissions and travel time, ultimately enhancing the quality of life for urban residents. Moreover, ITS can also promote the development of green transportation and reduce carbon emissions. With the increasing awareness of environmental protection, many countries are promoting green transportation modes such as bicycles, electric vehicles and public transportation. By providing intelligent transportation services that integrate multiple modes of transportation and optimise travel routes, ITS can effectively encourage people to choose more environmentally friendly transportation options, thus promoting sustainable urban mobility. Diverse transportation modes are crucial for effective traffic management, lowering congestion, enhancing safety and offering a variety of transportation options to fulfil the requirements of people and communities. In summary, the rapid development of transportation systems and the subsequent increase in traffic pressure necessitate the adoption of intelligent transportation systems. By promoting sustainable transportation, improving traffic efficiency and reducing carbon emissions, ITS not only improves the quality of urban life but also contributes to the global efforts towards sustainable development.

By 2019, China's car ownership has exceeded 300 million (Zemrane et al., 2021), four times as many as before. Without effective traffic congestion monitoring, large-scale accidents (Gao et al., 2021) are likely to occur. The most important thing for intelligent traffic congestion discrimination is to effectively grasp the traffic information so as to make intelligent judgments (Mirboland and Smarsly, 2021). The early intelligent traffic congestion identification technology mainly relied on GPS and other terminals, which were installed on the vehicle to carry out sensor positioning identification. However, the installation cost of GPS terminals was high, so many vehicles without such terminals could not be effectively identified (Hatzivasilis et al., 2021), resulting in identification gaps, resulting in poor recognition results.

The research on traffic congestion recognition in foreign countries began early. In the middle and late 20th century, the relevant California algorithm (Neogi et al., 2021) was proposed. This algorithm can compare the occupancy status of vehicles and roads, and effectively judge the road congestion. In the late 20th century (Syedyusuff et al., 2021), the relevant researchers also proposed the McMaster algorithm (Chan et al., 2021) to compare the relationship between road traffic flow, and effectively predict intelligent traffic congestion. There is little research related to it in China, and it mainly focuses on road occasional congestion (Laa et al., 2021). In recent decades, relevant researchers in China proposed to predict traffic flow data through wavelet transform, effectively detect the occupancy of roads and thus solve urban road traffic accidents (Geetha et al., 2021), but most of the discrimination methods cannot show the vehicle status in detail, or intelligently distinguish the traffic congestion status. The overall accuracy is also relatively low.

In order to solve the existing urban traffic congestion problem and avoid serious sudden road traffic accidents, this paper designs an intelligent traffic congestion discrimination method based on the front-end data collection of wireless sensor network. The main structure of the article is as follows:

1) Design an intelligent traffic congestion discrimination method based on wireless sensor network front end data acquisition, and in order to improve the discrimination effectiveness of traffic congestion data, through the obtain traffic congestion data based on front-end data collection of wireless sensor network, it can reduce power consumption.
2) In order to meet the temporal and spatial change relationship of discrimination, the intelligent traffic congestion discrimination method designed in this paper.
3) Experiment preparation and experimental results and discussion.

2 Design of intelligent traffic congestion discrimination method based on wireless sensor network front end data acquisition

2.1 Obtain traffic congestion data based on front-end data collection of wireless sensor network

In order to solve the problem of poor discrimination effect caused by the distribution rule of vehicle time period when GPS terminal collects traffic congestion data, and improve the discrimination effectiveness of traffic congestion data (Manogaran and Tu, 2021), this paper obtains traffic congestion data from front-end data acquisition platform based on wireless sensor network. Wireless sensor network is a term of distributed network, which can adjust network parameters and the location of devices through wireless communication (Azadani and Boukerche, 2021). The intelligent traffic congestion discrimination method designed in this paper selects the front end of the cc430 wireless sensor network as the central receiving node, obtains the traffic wandering data (Ning et al., 2021) of different sections and transmits it to the intelligent traffic discrimination centre for further analysis. The front-end data collection process in a wireless sensor network requires significant amounts of power, and can quickly drain the battery life of sensors. The amount of data being collected, size and effectiveness of the implementation can all affect the amount of power consumed by a front-end data collection process. Data collecting includes the use of sensors or other equipment that needs a lot of power to function properly. Wireless transmission of the gathered data to a distant server or cloud platform is required. In order to reduce power consumption, researchers have been exploring the concept of combining the front-end data collection with the data transmission receiving node. The methods that can be used to achieve effective power management in data transmission receiving nodes include low-power wireless communication protocols, short-range communication, duty cycling, sleep or wake strategies, wake on event, data aggregation, adaptive transmission power and error control techniques. This approach allows for both active and passive processing of data, which can help to reduce the amount of power consumed during data collection and processing. Active processing involves performing calculations and analysis on the collected data in real-time, while passive processing involves storing the collected data for later analysis. By combining these two methods, the wireless sensor network can efficiently manage the flow of data and reduce the amount of power consumed by the sensors. Data aggregation and data compression are the two techniques for effectively managing data flow in a wireless sensor network. The cc430 wireless sensor network is a popular choice for this approach due to its efficient use of power and strong processing capabilities. For wireless sensor nodes, the cc430 platform's ultra-low power operation allows for longer battery life. It combines an RF transceiver and a potent microprocessor into a single chip. facilitating easy interoperability and connectivity with other systems and devices. And, a strong software ecosystem supports it. By utilising the cc430 platform and combining front-end data collection with the data transmission receiving node, researchers are able to significantly improve the performance of wireless sensor networks while reducing power consumption (Bagga et al., 2021). Limited energy supply, communication range restrictions, data transmission efficiency, node coordination, network scalability, environmental considerations and fault tolerance are some of the difficulties faced when trying to increase performance of a wireless sensor network while lowering power consumption. The architecture of the front-end data collection platform for traffic congestion of the wireless sensor network is shown in Figure 1 below.

It can be seen from Figure 1 that the above platform is mainly composed of intersection acquisition node (Mittal, 2021), processing module, central receiver and manual monitoring centre, which can effectively reduce the acquisition interference of intersection data (Jolfaei et al., 2021) and improve the identification effect of traffic congestion.

The magnetic field distribution of different detection areas is constantly changing due to various environmental factors such as the presence of nearby electromagnetic devices, changes in temperature and humidity and alterations in the surrounding materials. Owing to the factors such the movement of ferromagnetic objects, changes in the magnetic properties of materials, fluctuations in external magnetic fields, electromagnetic interference and the shape of the detection area, the magnetic field distribution of various detecting areas is continually changing. These changes can affect the performance of the sensors, causing them to produce inaccurate readings and reducing their overall effectiveness. Furthermore, the magnetic field generated by different objects or materials can vary based on their composition and properties. Permanent magnets, electromagnets, ferromagnetic materials, paramagnetic materials, diamagnetic materials and superconductors are instances of objects or materials that produce magnetic fields based on their composition and qualities. For example, ferromagnetic materials have a much stronger response to magnetic fields than non-magnetic materials such as plastic or glass. A higher interaction and response between the magnetic field and the ferromagnetic material results from these magnetic moments' alignment with and strengthening of the external magnetic field are the main advantage of magnetic fields that allows them to react to them more efficiently than non-magnetic materials. As a result, the magnetic field distribution in the detection area can vary widely depending on the types of materials present. Owing to the elements including their sensing technology, range, sensitivity and deployment design, the types of sensors utilised can have a considerable impact on the detection area of a wireless sensor network. To compensate for these variations, it is important to calibrate the sensors regularly and ensure that they are properly configured for the specific application. This may involve adjusting the sensitivity and threshold levels of the sensors, as well as taking into account any environmental variables that may be affecting the magnetic field distribution. Environmental variables such as nearby magnetic sources, electromagnetic interference, temperature, humidity and surrounding materials can affect the magnetic field distribution by altering its strength and direction. By doing so, the sensors can provide more accurate and reliable measurements of the magnetic field, improving the effectiveness of the detection system. Therefore, this paper uses the HMC588 wireless sensor to improve the sensitivity of data acquisition (Montoya-Torres et al., 2021), and adjusts it through the data acquisition software. The HMC588 wireless sensor (HMC5883L)'s main features include a 3-axis magnetometer for monitoring magnetic fields, a wide measurement range for varied field strengths, high accuracy and resolution digital output interface (usually I2C), Flexible applications in navigation, robotics and magnetometry, built-in calibration for precise data and low-power consumption. The program structure of the data acquisition software is shown in Figure 2 below.

It can be seen from Figure 2 that using the above data acquisition software solution and the selected wireless sensor front-end data acquisition platform can effectively obtain intelligent traffic congestion discrimination data (Kyamakya et al., 2021; Wang et al., 2022) to ensure the accuracy of the final discrimination effect.

Figure 1 Wireless sensor front-end collection platform for traffic congestion data

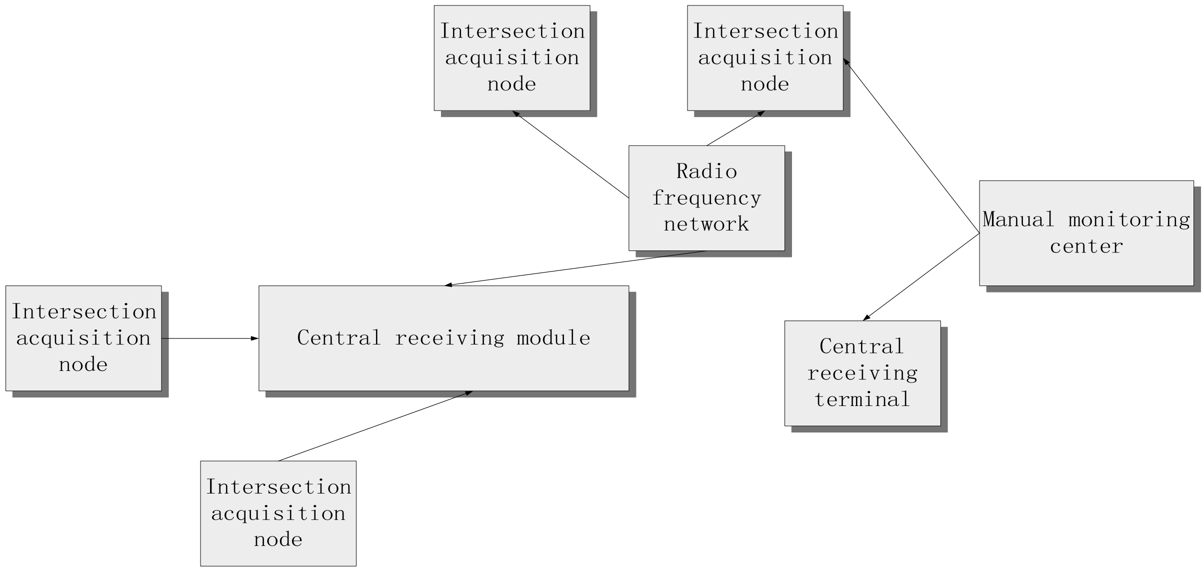
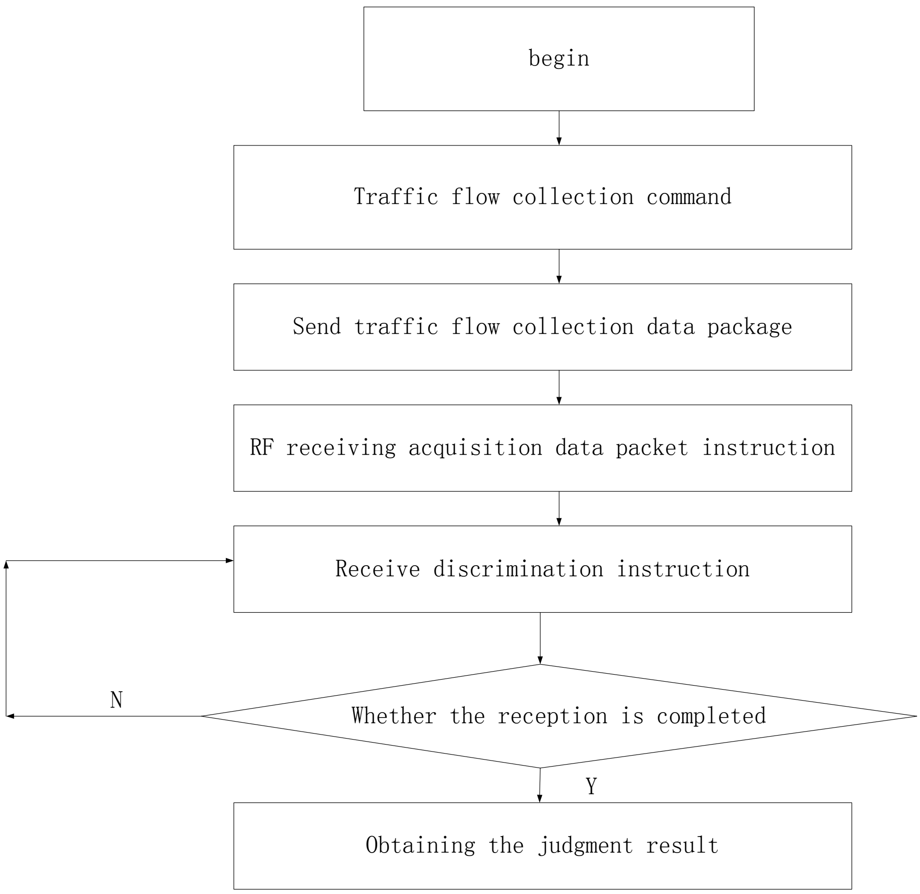


Figure 2 Program structure of data acquisition software



2.2 Design intelligent traffic congestion discrimination algorithm

In combination with the above intelligent traffic congestion data collection platform, in order to meet the temporal and spatial change relationship of discrimination, the intelligent traffic congestion discrimination method designed in this paper includes an effective intelligent traffic congestion discrimination algorithm. Real-time accurate identification and differentiation of various traffic congestion levels is the core goal of intelligent traffic congestion discrimination. This knowledge is essential for efficient traffic management and control because it enables the implementation of plans for reducing congestion, enhancing traffic flow and enhancing overall transportation effectiveness. Real-time traffic monitoring, effective traffic management, improved safety, decreased travel times and fuel consumption, increased environmental sustainability and improved performance of the transportation system overall are benefits of using Intelligent Transportation Systems (ITS) in the process of reducing traffic congestion. There are different traffic flow characteristics in different time periods (Wen et al., 2021), so the intelligent traffic congestion discrimination algorithm designed in this paper starts with the traffic flow characteristic parameters (Nambajemariya and Wang, 2021; Attari et al., 2021), conducts a comprehensive analysis and first calculates the traffic flow of a road Q, as shown in (1) below. Following are diverse traffic flow characteristics for various time periods when using intelligent traffic congestion discrimination algorithms. Peak Hours, Off-Peak Hours at off-peak periods with less traffic, Transition Periods between peak and off-peak hours, increased or decreased traffic volume depending on the event and less vehicles on the road at night.

$$Q = \frac{N}{T} \tag{1}$$

In formula (1), N represents the number of vehicles passed in the acquisition cycle (Amini et al., 2021; Qin and Zhang, 2021; Sharma et al., 2021), T represent the traffic flow, and the speed of vehicles running on the road V as shown in (2) below:

$$V = \frac{\sum_{i=1}^{N} V_i}{N} \tag{2}$$

In formula (2), V_i represents the instantaneous speed of vehicles. In order to test the average driving relationship of vehicles in a certain section, it is necessary to calculate the average driving time $\overline{V}$, as shown in (3) below:

$$\overline{V} = \frac{NL}{\sum_{i=1}^{N} T_i} \tag{3}$$

In formula (3), L represents the instantaneous speed of the vehicle, T_i represents the collection time (Chen et al., 2021). The temporal and spatial changes of vehicles are related to traffic density, so it is also necessary to calculate the space occupancy of traffic density O_S, as shown in (4) below:

$$O_S = \frac{\sum_{i=1}^{N} L_i}{L} \tag{4}$$

In formula (4), L_i represents the length of the vehicle. During the specified collection period, the time cumulative value of the vehicle volume also has an important impact on the identification of traffic congestion, so it is necessary to further calculate the time cumulative value of the vehicle O_t, as shown in (5) below. In order to identify locations with extended vehicle blockages, which indicate congestion, traffic congestion detection uses the vehicle block's time accumulation value. A greater chance of congestion is suggested by higher time accumulation values. Effective traffic congestion detection and management are made possible by analysing this value.

$$O_t = \frac{\sum_{i=1}^{N} T_i}{T} \tag{5}$$

Combined with the above parameters, an intelligent traffic congestion discrimination algorithm can be generated E, as shown in (6) below:

$$E = \overline{V} \times O_t \tag{6}$$

In formula (6), E represents that using the above intelligent traffic congestion identification method can effectively obtain traffic congestion parameters, generate relevant traffic congestion levels and ensure the accuracy of final identification to the greatest extent. The appropriate traffic congestion levels of low, moderate, high and severe congestion can be produced through the application of an intelligent method for identifying congestion in traffic.

3 Experiment

In order to verify the discrimination effect of the designed intelligent traffic congestion discrimination method based on wireless sensor network front-end data collection, this paper selects the experimental road sections that meet the experimental requirements, compares them with conventional intelligent traffic congestion discrimination methods and conducts experiments, as follows.

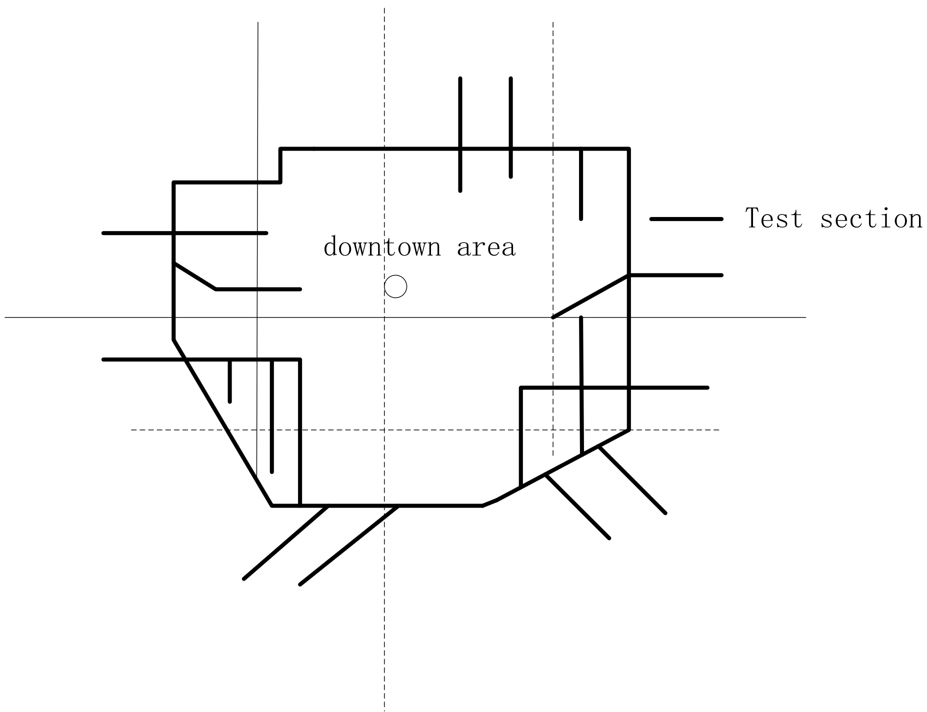
3.1 Experiment preparation

In this paper, the traffic road in the central area of a city is selected for the intelligent traffic congestion discrimination experiment. A central city roadway is chosen for the intelligent traffic congestion discrimination experiment based on variables including traffic volume, congestion levels, representative road characteristics, accessibility and availability of necessary infrastructure for data collecting and analysis. It is known that this road belongs to the basic urban expressway and has three different road operation modes, which meets the requirements of the experimental road. The distance between the experimental road and the city centre is 5.6 km, and the total length is 35.86 km. This statistic offers important details regarding the size and reach of the road network by offering insight into its overall breadth and coverage. The schematic diagram of the experimental road section is shown in Figure 3 below.

It can be seen from Figure 3 that the experimental road section is crisscrossed horizontally and vertically, and the pavement structure is complex, so the requirements for the identification of vehicle running speed and vehicle running data are high. The running speed of the entire experimental road section can be divided into three time periods, one is the working day period, the second is the weekend period and the third is the holiday period. The above time periods can be combined for comprehensive adjustment. Use Python Platform to input experimental road information, and use folium package to complete experimental development. In order to improve the accuracy of road information and show the longitude and latitude relationship of vehicles, this paper also uses folium package to visualise the longitude and latitude data. The Folium package's main features enable the experimental development and display of longitude and latitude data by interactivity, data point representation, make shapes and lines, produce maps, visualise data density, manage various overlays and layers and include interactive popup.

In combination with the spatio-temporal characteristics of vehicle operation on the experimental road section and the spatio-temporal planning of the road section, in order to ensure the integrity of the experiment, it is necessary to select the continuous operation data of vehicles to ensure the integrity of the data on each road section. This means that in order to obtain accurate and reliable data from the experiment, it is important to carefully consider the spatio-temporal characteristics of the vehicles being used and the road section being studied. This includes selecting a specific time period during which the vehicles will operate and collecting continuous data throughout this period. By doing so, researchers can ensure that they have a complete set of data for each segment of the road, which will allow them to accurately analyse the results of the experiment. Additionally, it may be necessary to plan the route of the vehicles so as to avoid any potential interruptions or deviations from the intended path. Real-time traffic conditions, weather forecasts and any known road closures or accidents should all be taken into account when planning a route for a vehicle to avoid potential delays or deviations from the intended course. This planning should take into account factors such as traffic patterns, road conditions and any other relevant spatial or temporal factors. Overall, careful planning and data collection are essential for ensuring the success and accuracy of the experiment.

Figure 3 Schematic diagram of experimental road section



After the data collection is completed, the DDGY model is used for sealing processing, which assumes that the data node is 10 and the data is always in the average driving state. The DDGY model carries out the following functions, including measuring and recording electric energy consumption, monitors and tracks energy usage by displaying metering data, observes the properties of electrical loads for study and improvement, enables data transmission for additional analysis or billing needs, utilises established tariff rates to calculate energy expenses and control electrical loads. This model helps to ensure the integrity of the experiment by filling in any missing data and correcting any irregularities or anomalies. The spatio-temporal characteristics of the vehicle operation on the experimental road section are also taken into consideration while selecting the continuous operation data of vehicles. Optimal route planning and dynamic adaptability to changing conditions are benefits of employing spatio-temporal planning. This helps to ensure accuracy and consistency in the data collected. Additionally, the spatio-temporal planning of the road section is also crucial in ensuring that the experiment is conducted smoothly and efficiently. Overall, a well-planned and executed experiment can yield valuable insights and contribute to the advancement of knowledge in the field.

It can be seen from Table 1 that the above experimental road data are mainly from the Gaiya road data processing platform, which includes all road traffic operation data of the experimental road from 2020. 5 to 2020. 9.1, as well as the TTI traffic index and average speed of the road. In order to improve the balance of data, the experimental platform selected the designated road travel time interval and compressed all road data into the city-district.txt (urban TTI road experiment data), boundary.txt (road collection range WKT coding data) and road.txt (average vehicle driving data) files.

Table 1 Test road data sample

Statistical time	*Road ID*	*Road range*	*Velocity (km\h)*
2020\7\2\0:00:00	263317	West Second Ring Road; North Third West Road, Second Ring South Road	57.842
2020\7\2\0:00:00	263745	East Section of Second Ring South Road; Jiangong Road; Northwest Middle Road	45.4325
2020\7\2\0:00:00	263713	Second Ring North Road; Southwest Road; Central Expressway	58.5139
2020\7\2\0:00:00	263868	Beifu Road, Second Ring Road; Southwest Road; Dongbei Road	42.3658
2020\7\3\0:00:00	263725	3rd Ring Rd; Third Ring Middle Road; Second Ring East Road	48.2546
2020\7\3\0:00:00	263848	Second Ring South Road; Second Ring East Road; Second Ring West Road	51.6523
2020\7\3\0:00:00	263762	Second Ring South Road Auxiliary Road; Municipal Middle Road; Beisan Road	53.2698
2020\7\3\0:00:00	263823	Second Ring East Road; Second Ring South Road; First Ring Road	34.1572
2020\7\4\0:00:00	263184	First Ring Road; Second Ring Middle Road; Second Ring North Road	35.2847
2020\7\4\0:00:00	263285	Second Ring East Road Auxiliary Road; Second Ring South Road; North 1st Ring Road	38.2654
2020\7\4\0:00:00	263351	Second Ring East Road Auxiliary Road; Southwest Road; Southwest Middle Road	34.2617
2020\7\4\0:00:00	263549	Second Ring East Road Auxiliary Road; University Road; Northwest Road	34.2654
2020\7\5\0:00:00	263384	Main road; East-west horizontal and vertical intersection; North South Passage	29.3654
2020\7\5\0:00:00	263463	3rd Ring Rd; Second Ring Road; Northwest Road	52.3641
2020\7\5\0:00:00	263326	West Second Ring Road; West Third Ring Road; Beisan Middle Road	56.2359
2020\7\5\0:00:00	263318	Beiyi’er Road; Northwest Auxiliary Road; Southwest Middle Road	47.2811
2020\7\5\0:00:00	263374	Second Ring South Road Auxiliary Road; Northwest Middle Road; Southwest Auxiliary Road	57.5754
2020\7\6\0:00:00	263423	Second Ring East Road; 3rd Ring Rd; Second Ring South Road	57.4986

According to the requirements of the experiment, this paper uses the WTK road geospatial OGC language as an intelligent markup language to express the geometric space characteristics of the experimental road.

MultLineString data is a type of geospatial data format that represents multiple line segments in a single object. Generally, the maximum number of characters that can be stored as road networks in a MultiLineString data structure is not predetermined. The underlying storage system or database being used, as well as its capabilities and limitations, will determine the storage capacity. It is commonly used to represent road networks, where each line segment represents a specific segment of the road. In the case of the WTK data, this means that each MultLineString object represents a specific segment of a road or highway. To ensure the accuracy of the experiment, it is important to select a time period during which the road network is representative of typical traffic conditions. In the case of this paper, the experiment was conducted using road data from July. This time period was chosen for several reasons. Firstly, July is typically a month with average traffic patterns and road conditions. Compared to peak traffic periods such as holidays or major events, the traffic volume in July is relatively stable and consistent. This provides a good baseline for the experiment, as it allows researchers to accurately measure the impact of the experimental variables on normal traffic patterns. Secondly, selecting data from July helps to avoid the interference of long holiday periods on the experimental data. Holidays such as Chinese New Year or National Day can significantly disrupt traffic patterns and make it difficult to obtain accurate data. By selecting data from July, the experiment can avoid these potential sources of interference and provide more reliable results. Overall, selecting a representative time period for the experiment is crucial for ensuring the accuracy and relevance of the data. By choosing data from July, the paper is able to more effectively analyse the impact of the experimental variables on the road network. Traffic volume, traffic flow distribution, traffic speed, road capacity, road layout and traffic control techniques are some of the experimental variables in a traffic congestion algorithm on a road network.

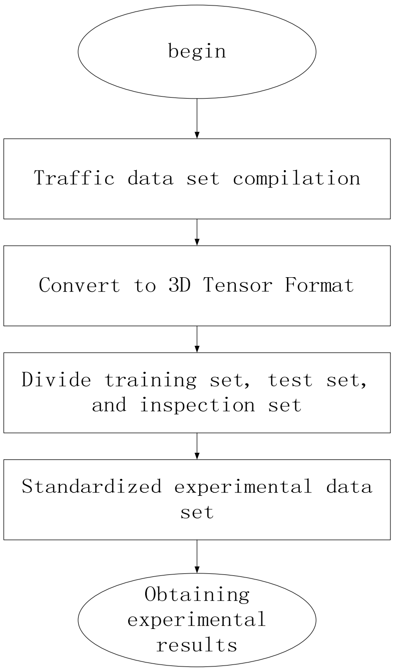
After the data processing is completed, the Radial Basis Function (RBF) neural network needs to be used for data training to sort out the data into a format that meets the needs of the experiment, and then sort out the data to reduce the comprehensive search time of the experiment. The input layer, radial basis function layer, weights, centres and spread/width parameters are the key components of the RBF neural network. The collation of different experimental data requires that there are certain differences between villages, and it needs to be comprehensively sorted out according to the temporal and spatial change relationship of roads. It is challenging to compare the spatial component and the temporal factor since they use different types of data (location vs. time) and call for different measurement techniques. It is also difficult to compare their influence on a system or phenomenon directly because of the way they interact. Taking some travel data as an example, their spatio-temporal characteristics are shown in Table 2 below.

It can be seen from Table 2 that the data of the same road section at different times has a temporal and spatial variation relationship. The average value can be used to replace the subsequent experimental variables to improve the accuracy of the experiment. The experimental process at this time is shown in Figure 4 below.

Table 2 Temporal and spatial characteristics of data

Time	*A section of a highway or railway ID*	*V*	*V-T*	*VW*	*X*	*Real results*
2020\7\14\0:20	263915	53.1278	53.0727	55.4412	870	52.275
2020\7\14\0:30	363915	52.275	53.1273	55.5405	873	54.4155
2020\7\14\0:40	363915	54.4155	52.275	55.9756	870	55.7623
2020\7\14\0:50	363915	55.7623	54.4155	55.4266	871	56.8314
2020\7\14\1:00	363915	56.8314	55.7623	55.6887	871	56.2899
2020\7\14\1:10	363915	56.2899	56.8314	57.2452	865	56.9541
2020\7\14\1:20	363915	56.9541	56.2899	57.2644	874	60.189
2020\7\14\1:30	363915	60.189	56.9541	58.9952	873	58.1973
2020\7\14\1:40	363915	58.1973	60.189	57.8362	873	58.7059

Figure 4 Experimental process



In combination with the experimental process in Figure 4, we can further obtain the intelligent traffic congestion discrimination data for subsequent discriminant analysis.

3.2 Experimental results and discussion

In combination with the above experimental road data and experimental requirements, intelligent traffic congestion discrimination experiments can be conducted, that is, intelligent traffic congestion discrimination methods based on wireless sensor network front-end data collection and conventional intelligent traffic congestion discrimination methods designed in this paper are used to conduct intelligent traffic congestion discrimination, and the discrimination effects of the two methods under different roads are recorded. The experimental results are shown in Table 3 below.

It can be seen from Table 3 that the intelligent traffic congestion discrimination results of the intelligent traffic congestion discrimination method designed in this paper based on the front-end data collection of wireless sensor network in different roads are consistent with the actual results, while the conventional intelligent traffic congestion discrimination methods have many unidentifiable situations. It is proved that the intelligent traffic congestion discrimination method designed in this paper based on wireless sensor network front-end data collection has good discrimination effect, reliability and certain application value, and has made certain contributions to solving traffic congestion problems.

Table 3 Experimental results

Road ID	*Vehicle density (vehicle lane m)*	*Vehicle speed (km\h)*	*congestion index*	*Congestion level*	*Determine congestion level*
The intelligent traffic congestion detection method designed in this paper based on front-end data collection of wireless sensor networks					
263317	0.015	3.69	1.5	No obvious congestion	No obvious congestion
263745	0.028	3.54	2.0	Slight congestion	Slight congestion
263713	0.036	3.05	2.2	Occasional congestion	Occasional congestion
263868	0.062	2.94	2.4	Frequent congestion	Frequent congestion
263725	0.098	2.56	2.6	Moderate congestion	Moderate congestion
263848	0.135	2.04	3.1	Heavy congestion	Heavy congestion
Conventional intelligent traffic congestion discrimination methods					
263317	0.015	3.69	1.5	No obvious congestion	Unrecognised
263745	0.028	3.54	2.0	Slight congestion	Unrecognised
263713	0.036	3.05	2.2	Occasional congestion	Unrecognised
263868	0.062	2.94	2.4	Frequent congestion	Frequent congestion
263725	0.098	2.56	2.6	Moderate congestion	Moderate congestion
263848	0.135	2.04	3.1	Heavy congestion	Unrecognised

4 Conclusion

In the context of urban development, China's transportation system is becoming more and more perfect, and the per capita car ownership is also getting higher and higher, which brings convenience to people's daily life and also causes many problems, and traffic congestion accidents emerge in endlessly. Once the traffic congestion of the road is not effectively monitored and judged, the problem of road operation congestion will easily occur, leading to large-scale traffic accidents. Therefore, an intelligent traffic congestion discrimination method needs to be designed. Conventional intelligent traffic congestion discrimination methods have poor discrimination effect and cannot meet the traffic timing requirements. Therefore, this paper designs a new intelligent traffic congestion discrimination method based on wireless sensor network front-end data collection. The experiment results show that the designed intelligent traffic congestion discrimination method has good discrimination effect, reliability and certain application value and has made a certain contribution to reducing the frequency of road accidents.

References

Amini, M., Hatwagner, M.F. and Mikulai, G.C. et al. (2021) 'An intelligent traffic congestion detection approach based on fuzzy inference system', *Proceedings of the IEEE 15th International Symposium on Applied Computational Intelligence and Informatics (SACI)*, IEEE, Romania.

Attari, M., Ejlaly, B. and Heidarpour, H. et al. (2021) 'Application of data mining techniques for the investigation of factors affecting transportation enterprises', *IEEE Transactions on Intelligent Transportation Systems*, pp.1–16.

Azadani, M.N. and Boukerche, A. (2021) 'Driving behavior analysis guidelines for intelligent transportation systems', *IEEE Transactions on Intelligent Transportation Systems*, pp.1–19.

Bagga, P., Das, AK. and Wazid, M. et al. (2021) 'On the design of mutual authentication and key agreement protocol in internet of vehicles-enabled intelligent transportation system', *IEEE Transactions on Vehicular Technology*, pp.1–1.

Chan, R., Lim, M.Y. and Parthiban, R. (2021) 'A neural network approach for traffic prediction and routing with missing data imputation for intelligent transportation system', *Expert Systems with Applications*, Vol. 171, No. 2. Doi: 10.1016/j.eswa.2021.114573.

Chen, K., Hu, L. and Yao, M. et al. (2021) 'Study on intelligent traffic search method based on driver facial feature analysis', *International Journal of Vehicle Information and Communication Systems*, Vol. 6, No. 2, pp.151–160.

Gao, M., Wang, J. and Chen, Y. et al. (2021) 'An improved multi-exposure image fusion method for intelligent transportation system', *Electronics*, Vol. 10, No. 4. Doi: 10.3390/electronics10040383.

Geetha, V., Gomathy, C.K. and Harshitha, T. et al. (2021) 'A traffic prediction for intelligent transportation system using machine learning', *International Journal of Engineering and Advanced Technology*, Vol. 10, No. 4, pp.166–168.

Hatzivasilis, G., Fysarakis, K. and Ioannidis, S. et al. (2021) 'SPD-safe: secure administration of railway intelligent transportation systems', *Electronics*, Vol. 10, No. 1. Doi: 10.3390/electronics10010092.

He, S., Yang, X. and Liao, Y. (2021) 'Improved Tomlinson–Harashima precoding for ultra reliable communication in intelligent transportation systems', *Complexity*, No. 6, pp.1–10.

Jolfaei, A., Menon, V.G. and Chen, L. et al. (2021) 'Guest editorial advanced sensing and sensor fusion for intelligent transportation systems', *IEEE Sensors Journal*, Vol. 21, No. 14, pp.15425–15426.

Kyamakya, K., Chedjou, J.C. and Al-Machot, F. et al. (2021) 'Intelligent transportation related complex systems and sensors', *Sensors*, Vol. 21, No. 6. Doi: 10.3390/s21062235.

Laa, I., Sanchez-Medina, J.J. and Vlahogianni, E.I. et al. (2021) 'From data to actions in intelligent transportation systems: a prescription of functional requirements for model actionability', *Sensors*, Vol. 21, No. 4. Doi: 10.3390/s21041121.

Manogaran, G. and Tu, N.N. (2021) 'Displacement-aware service endowment scheme for improving intelligent transportation systems data exchange', *IEEE Transactions on Intelligent Transportation Systems*, pp.1–11.

Mirboland, M. and Smarsly, K. (2021) 'BIM-based description of intelligent transportation systems for roads', *Infrastructures*, Vol. 6, No. 4. Doi: 10.3390/infrastructures6040051.

Mittal, S. (2021) 'Secure V2V and V2I technologies for the next-generation intelligent transportation systems', *Computer*, Vol. 54, No. 2, pp.4–6.

Montoya-Torres, J.R., Moreno, S. and Guerrero, W.J. et al. (2021) 'Big data analytics and intelligent transportation systems', *IFAC-PapersOnLine*, Vol. 54, No. 2, pp.216–220.

Nambajemariya, F. and Wang, Y. (2021) 'Excavation of the internet of things in urban areas based on an intelligent transportation management system', *Advances in Internet of Things*, Vol. 11, No. 3, pp.113–122.

Neogi, N., Bhattacharyya, S. and Griessler, D. et al. (2021) 'Assuring intelligent systems: contingency management for UAS', *IEEE Transactions on Intelligent Transportation Systems*, pp.1–11.

Ning, Z., Sun, S. and Wang, X. et al. (2021) 'Blockchain-enabled intelligent transportation systems: a distributed crowdsensing framework', *IEEE Transactions on Mobile Computing*, pp.1–1.

Pu, X. and Luo, W. (2021) 'Research on intelligent transportation logistics technology based on energy saving and emission reduction', *IOP Conference Series: Earth and Environmental Science*, Vol. 781, No. 3. Doi: 10.1088/1755-1315/781/3/032020.

Qin, H. and Zhang, H. (2021) 'Intelligent traffic light under fog computing platform in data control of real-time traffic flow', *The Journal of Supercomputing*, Vol. 77, No. 4, pp.1–23.

Sharma, M., Bansal, A. and Kashyap, V. et al. (2021) 'Intelligent traffic light control system based on traffic environment using deep learning', *IOP Conference Series: Materials Science and Engineering*, Vol. 1022, No. 1. Doi: 10.1088/1757-899X/1022/1/012122.

Syedyusuff, S., Subramaniam, R. and Vijay, R. (2021) 'Orthogonally integrated hybrid antenna for intelligent transportation systems', *Applied Computational Electromagnetics Society Journal*, Vol. 36, No. 5, pp.519–525.

Wang, S., Pei, Z. and Wang, C. et al. (2022) 'Shaping the future of the application of quantum computing in intelligent transportation system', *Intelligent and Converged Networks*, Vol. 2, No. 4, pp.259–276.

Wen, C., Habib, A.F. and Li, J. et al. (2021) 'Special issue on 3D sensing in intelligent transportation', *IEEE Transactions on Intelligent Transportation Systems*, Vol. 22, No. 4, pp.1947–1949.

Yadav, S. and Rishi, R. (2021) 'Secure and authenticate communication by using SoftSIM for intelligent transportation system in smart cities', *Journal of Physics: Conference Series*, Vol. 1767, No. 1. Doi: 10.1088/1742-6596/1767/1/012049.

Zemrane, H., Baddi, Y. and Hasbi, A. (2021) 'Mobile ad hoc network routing protocols for intelligent transportation systems', *International Journal of Smart Security Technologies*, Vol. 8, No. 1, pp.35–48.

Zeng, Y., Sun, C. and Zhang, L. et al. (2021) 'Data collection and processing framework for operation monitoring based on big data technology', *Computer Simulation*, Vol. 38, No. 7, p.8.