ISSN 1330-3651(Print), ISSN 1848-6339 (Online)
https://doi.org/10.17559/TV-20240227001353
Original scientific paper

Research on Intelligent Traffic Congestion Degree Collaborative Algorithm and Path Planning Based on Sensor Data

Hanzheng SUN*, Xuejing ZHANG, Dan LI, Jianling TAN

Abstract: Urban road traffic congestion has become a major problem that hinders the rapid and healthy development of cities. In this paper, the heterogeneous congestion network is divided into multiple congestion proton regions and boundary subregions by the double-layer partition method, and the traffic flow balance model of multi-regional network is established based on the macro basic map. A layered traffic management architecture based on multi-agent is designed, which provides a new method to improve the efficiency of urban traffic signal control. The wireless sensor network is deeply studied, and the path of the most critical factor affecting the transportation cost in the site construction model is studied in detail by tabu algorithm. According to the traffic network and real-time road condition information, the road network is abstracted as a graph based on the principle of graph theory, and the shortest path algorithm in graph theory is used to avoid obstacles and search for the optimal path, which can make drivers understand the road condition information in real time and make route decisions.

Keywords: intelligent transportation; path planning; sensor; traffic congestion coordination

1 INTRODUCTION

Changes in sensor technology, high-speed data transmission, bring people closer to each other and change the way people interact [1] Sensor network integrates computer technology, sensor technology and modern communication technology, establishes a connection between the logical information world and the objective physical world, and inputs perceptual data from the physical world to the logical world in order to better process data and understand the world [2, 3]. Although the characteristics of traffic congestion vary between different cities or between different areas of the same city, the surge of traffic flow will further stimulate the spread of congestion to its closely related adjacent sections. With the continuous expansion of congestion time and scope, traffic congestion presents a development trend from point to line to surface, and the resulting regional traffic congestion has become the "new normal" of traffic in large and medium-sized cities [4]. This seriously affects the quality of life of residents in congested areas, also puts forward higher requirements for urban road traffic management.

The causes of urban traffic congestion are complicated, which is fundamentally due to the serious imbalance between traffic supply and traffic demand [5]. Therefore, to solve the traffic congestion problem, we must strive towards the dynamic balance between traffic supply and traffic demand, and adopt a multi-pronged strategy, that is, increase the capacity of the traffic system by building new road traffic infrastructure or rebuilding and expanding traffic bottleneck sections. By vigorously developing public transportation and guiding residents to change their travel modes, the utilization efficiency of transportation system resources should be improved without changing the total demand. Although the above strategies can alleviate congestion to a certain extent, they often have a long implementation period and are difficult to implement, and could not effectively solve the current congestion problem of urban traffic in a timely manner. With the continuous improvement of road traffic system control equipment, on the base of the implementation of strategic traffic congestion management measures, intelligent control means must be adopted at the same time to solve the problem of urban road traffic congestion, in order to obtain an effective balance between traffic demand and network capacity, and minimize the negative impact caused by congestion. At the same time, through data analysis and calculation and the use of relevant algorithms to solve the problems of urban station construction planning and urban traffic path planning, so that our data analysis and urban station construction and path planning are more efficient and reliable, which is an exploratory improvement to the traditional algorithm. Therefore, this paper has practical guiding significance in solving traffic congestion and urban path planning. By using advanced path planning algorithm and prediction technology to predict the road network condition in advance, the optimal path can be calculated according to the road network condition, and the multi-candidate path set with high stability is given with the least predictive configuration cost. The key technologies of road sensor configuration and multi-path planning in the prediction mechanism are studied.

2 RELATED WORK

Smooth, light congestion or congestion can use the relevant data collected to determine the true road conditions on the road. The real road is a one-way street in time periods, always a one-way street or a two-way street. Therefore, in environmental modeling, congestion weight and one-way and two-way road conditions are introduced into the model as variables [6], and point-to-point routing algorithm is improved. Make the best route selection for the new urban environment map model.

At present, domestic and foreign scholars have conducted a large number of studies on road traffic state parameter estimation and congestion detection. They have not only proposed parameter estimation methods [7] to characterize the traffic flow operating state, but also used various models or methods to distinguish road traffic congestion [8] on this basis, that is, to specifically analyze the operating state of road traffic at a certain moment and the degree of congestion. According to different selected traffic status parameters, traffic congestion detection methods can be divided into traffic congestion detection based on single parameters and traffic congestion detection based on mixed parameters [9], among which common single traffic status parameters include running speed, traffic flow density, queue length, travel time, delay and time share. War research work. If the rule-based pattern recognition method is introduced, the percentage of the speed lower than the free flow speed is regarded as deceleration [10]. Then the simple rules are gradually refined into heuristic rules. A pattern recognition method based on empirical mode decomposition is proposed [11], which decomposes the original speed data of floating vehicles into speed time series with different simultaneous frequencies to represent the speed change trend in short, medium and long term ranges, and is used to detect congestion events with different time granularity. The search algorithm is used to identify the traffic congestion mode from the floating vehicle speed data, divide the average speed into four qualitative states according to the service level of the trunk road [12], and define different traffic modes based on all possible combinations of states. The highway traffic congestion detection method based on deep learning [13] is superior to the traditional rule method, which not only significantly improves its universality, but also accurately estimates the duration of congestion events. Based on the license plate recognition data, the estimation methods of single-vehicle travel speed and interval average travel speed are proposed [14], and on this basis, the traffic congestion recognition methods are studied to achieve the accurate determination of the duration and type of congestion. Although traffic density is difficult to obtain directly, it is still an important indicator of congestion identification. A statistical method is adopted to solve the problem of road traffic state estimation and congestion detection [15]. A segmented exchange linear traffic flow model is introduced to build a hybrid observer for estimating road traffic density parameters. On this basis, combined with the hybrid observer and generalized likelihood ratio test, an effective traffic congestion detection method is proposed, which uses the exponential weighted moving average method [16] to organically integrate historical and real-time traffic information into decision rules, and significantly improves the detection ability of early changes in congestion. By analyzing the global motion of video data to directly estimate the macro parameters, a traffic density estimation method based on the macro parameters is proposed, and combined with the support vector machine classifier [17], road traffic congestion is divided into three categories: light, moderate and severe congestion.

With the choice of road planning, however, the assumptions of these traditional analytical methods cannot be effectively verified. With the improvement of data availability, more data are used for statistical regression analysis and overall planning of sites and paths, but these methods are still an exploration between hypothesis and test, and there is often a lot of controversy about their actual effect. At the same time, there are few related studies on the construction planning and transportation of automobile stations, but there are some related studies in other fields, using genetic annealing algorithm [18], genetic algorithm [19] linear programming method [20], neural network algorithm [21] and other algorithms. In graph theory, currently commonly used multipath planning algorithms can be divided into two categories: the proposed k shortest path algorithm [22] and the proposed completely disjoint path algorithm [23]. Then the candidate path set is generated by adding a large incremental weight to the path on the optimal path [24]. The non-similar path set is determined by measuring the spatial difference between any two paths in the path set [25]. This method finds some paths from the path set so that the minimum distance between any two paths in these paths is maximum. By gradually increasing the shortest path, these algorithms iteratively find the next suboptimal path [26] until the generated candidate path set satisfies some given conditions, such as the shortest time constraint. After the weight of the section, the new candidate path is iteratively calculated according to the increase [27]. Dotoli's algorithm was extended to find some candidate paths, and Dijkstra's shortest path had a limited number of two or three shared sections [28], and logarithmic weight increase method was adopted. However, there are still many shortcomings in the applicability and practical operation of these algorithms and practical problems. However, the above path planning algorithms all have some drawbacks, and their calculation is too cumbersome, which inevitably prolongs the response time, especially when the road network is huge, the traffic load is crowded, and the traffic changes greatly. These algorithms need to adjust the link weight of the generated optimal path, and then repeatedly use Dijkstra's algorithm to calculate the suboptimal path, which leads to a heavy computational burden. In addition, these algorithms generally involve only the path planning of a single vehicle, but it is necessary to consider the paths of all vehicles on the urban road network at the same time.

3 RESEARCH ON SENSOR-BASED INTELLIGENT TRAFFIC CONGESTION COLLABORATIVE ALGORITHM

3.1 Road Traffic Sensors Monitor and Automatically Track Congested Roads

Traffic congestion is not only a purely technical problem, but also involves a series of problems such as economy, environment, residence, culture and administration. Tab. 1 summarizes the main factors of traffic congestion in big cities of our country.

Table 1 Analysis table of urban road traffic congestion factors

Acceleration of urban progress	The urban layout is unreasonable Rapid growth of motor vehicles Slow development of public transportation
Mode of transportation constitutes an imbalance	Road passenger transport market is more chaotic
Unbalance of road structure	Urban road infrastructure development lags behind
Backward traffic management	The planning and layout of transportation facilities lacks scientificity and predictability
Traffic law education lags behind	Modern traffic awareness is lacking

After receiving the real-time road congestion information sent by the information acquisition system, the sensor background processing computer finds out the camera and its preset bit corresponding to the congested road number contained in the information through the road webcam-preset mapping table, and then generates the corresponding control command to send to the TV

(Velocity Sensor) monitoring control host; the TV monitoring control host controls the corresponding camera to turn to the corresponding preset bit according to the received control instruction to show the condition of the crowded road section. Because the same camera is responsible for monitoring more than one road section, and the degree of congestion of each road section within the monitoring range is different, the priority is arranged in the design of automatic tracking. The design idea is: the section congestion information contains the section congestion code, the background processing computer will have received each section of information congestion degree comparison, in accordance with the order of serious, moderate and mild to determine the priority of the camera should rotate the direction, and then according to the most priority rotation direction to generate control instructions sent to the TV monitoring control host.

Its organizational structure and logical relationship are shown in Fig. 1, covering three closely related layers, namely, data analysis layer, congestion identification layer and congestion control layer. The data analysis layer is the core basis of the congestion identification layer, and the quality of the traffic information it obtains is directly related to the accuracy of the congestion early warning identification. The congestion identification layer is the necessary premise of the congestion control layer, and its early warning and dynamic process are the key to realize the active control of traffic congestion. Congestion control layer is the specific application of the first two levels of content, and its control effect can be effectively fed back through the data analysis layer.

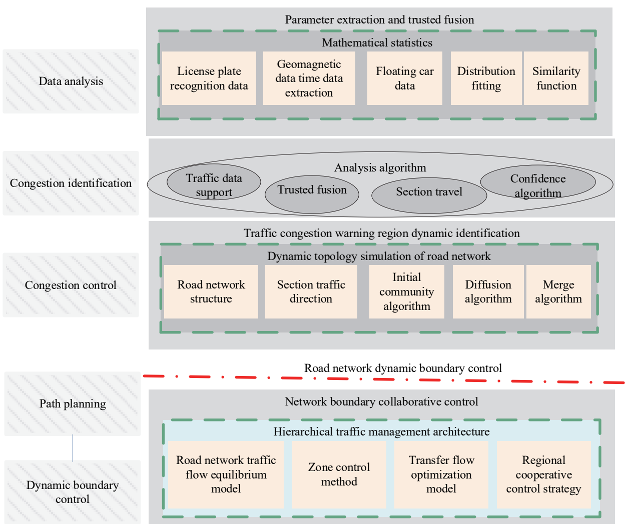

Figure 1 Research framework of congestion collaborative tracking algorithm monitored by road traffic sensors

3.2 Research on Cooperative Algorithm of Traffic Sensor Network

From the perspective of urban road traffic operation, road traffic can generally be divided into two states: smooth and crowded. Traffic congestion can also be divided into two types: unexpected congestion caused by traffic accidents and frequent congestion caused by traffic demand approaching or exceeding road bottleneck capacity. Under normal circumstances, traffic flow does not suddenly go from smooth to heavy. When the traffic volume gradually increases close to a certain critical value, the traffic state is bidirectional, which is called the critical traffic state. The critical traffic state may develop into a congested state or recover into a smooth state, which mainly depends on the timeliness and effectiveness of traffic management measures. The determination of the critical state can introduce a crowding threshold:

$$M_w = \frac{\sum_{i=1}^{n} t_i}{T_g}, t_i = d/v \tag{1}$$

where d is the distance between the two road sensor nodes, V is the speed at which the vehicle may pass through the road sensor nodes under crowded conditions, and Tg is the green time of the current cycle.

When a certain direction is given a green light, vehicles should normally file through the intersection quickly, and each vehicle should not occupy the detector for more than 2 seconds. When the detector is continuously occupied for more than 2 seconds, it can be considered that the vehicle is driving slowly due to congestion in front of it. All the time periods during which the flow direction is continuously occupied for more than 2 seconds are added up during the whole green light period, and the congestion is obtained compared with the green light.

The collaborative algorithm of traffic information collection and cooperative control network mainly includes two parts, and the traffic cooperative control network part mainly completes the receiving and processing of real-time traffic information. Some algorithms of traffic information collection are shown in Tab. 2.

Table 2 Collaborative Algorithms of traffic sensor networks (part)

```
F01, F02, F03;
Flag1 = False; Flag2 = False;
If E >= F01 t hen
Flags=True; i = 1;
while Flag1 == True&&I < 10
If E >= F01 then
Flag1 = True; i++;
Else
Flag1 = False;
If  i == 10 then
t2 = 1;
If E > E1 then
Flag2 = True; i = 1;
While Flag2 == && i < 10 do
If E > E2 then
Flag2 = True; i++;
Else
Flag2 = False;
If i == 10 then
v = 6/t2;
T = to + x/v;
Send the information to the intersection sensor node;
```

3.3 Sensor Intelligent Traffic Congestion Cooperation Algorithm Based on Two-Layer Partition

Assume that a single-region urban network consists of two parts: congestion protection zone 1 and regional boundary 2. Congestion protection zone 1 is the central area of a city, which usually attracts a large amount of traffic demand and tends to be saturated or supersaturated.

Zone boundary 2 is all signalized intersections around congestion protection Zone 1.

T is the simulation time interval or boundary control interval, and the simple conservation equation of congestion protection region 1 is used to describe the dynamic evolution of regional traffic flow:

$$n_1(k+1)=n_1(k)+T(Q_{\text{in}}(k)-Q_{\text{out}}(k)) \tag{2}$$

Assuming that there is no traffic flow generated or completed in the boundary section, that is, there is no entrance or exit setup in the boundary section, traffic flow detectors are installed in the upstream, middle and downstream of the section respectively, in which the two endpoint detectors mainly measure real-time traffic flow, and the middle detector mainly measures time occupancy. Based on this, Kalman filter is used to estimate queuing vehicles:

$$x_{1,m}(k+1)=x_{1,m}(k)+F(x_{1,m}(k)-q_{1,m}(k)) \tag{3}$$

where, m represents the m boundary road section around congestion protection area 1; x is the predicted number of queuing vehicles at the m boundary section within the k time step; u is the measured arrival flow of the m boundary section in the k time step; q is the measured departure flow of the m boundary section in the k time step.

The calculation formula of the measured queued vehicle x is as follows:

$$x_{1,m}(k)=n_{1,m}\frac{L_{\max}}{L_{\max}+\delta}\times Q_{1,m}(k) \tag{4}$$

For the congestion protection area within $k+1$ time step, the deviation value between the regional cumulant $n(k+1)$ and the optimal critical cumulant generation n is $D(k+1)$, which is calculated as follows:

$$D_m(k+1)=n_{1,m}(k+1)-n_{1,m-1}(k) \tag{5}$$

According to the deviation value, the signal timing optimization strategy based on dynamic boundary intersection is proposed, as shown in Fig. 2.

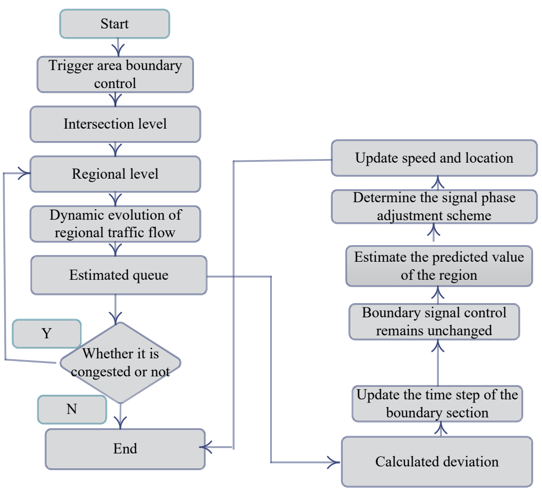

Figure 2 Signal timing optimization strategy of dynamic boundary intersection

To design an effective algorithm, consider the following:

1) The number of stations and obstacles is limited. The environment is finite and closed.
   The points and termination points are known.
2) The search time and search path are as minimal as possible.
3) The location and size of sites and obstacles can be accurately located and analyzed by wireless sensor networks.
4) The path planning algorithm design should be systematic and structured to avoid the complexity of conditions and events.

When $D(k+1)=0$, the boundary intersection signal control of congestion protection region 1 remains unchanged. When $D(k+1)>0$, the deviation value is treated as a boundary input restricted stream in $k+1$ time step, and the total number is allocated to $M(k+1)$ dynamic boundary controlled points.

The duration is 4 h and the simulation step length is 18 s. Fig. 3 shows the repeated simulation experiments of 5 groups of discrete points with different colors corresponding to different random seeds. Each discrete point represents the accumulated traffic volume and travel completion flow every 160 s in the experimental area. According to the data of all discrete points, the yellow solid line in Fig. 3, the corresponding curve fitting results reach the peak when the regional accumulation is equal to 14000 vehicles, and the trip completion rate is the largest. Therefore, the optimal critical cumulant is set as 14000 vehicles in the dynamic boundary control strategy.

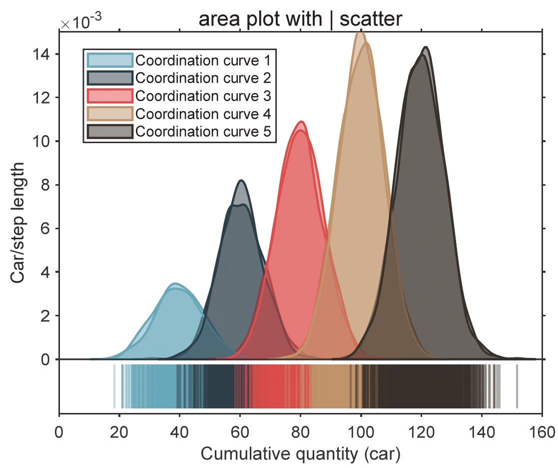

Figure 3 Intelligent traffic congestion coordination curve of sensors in two-layer partition

4 RESEARCH ON INTELLIGENT TRAFFIC PATH PLANNING BASED ON MULTI-SENSOR INFORMATION FUSION

4.1 Path planning mechanism based on multi-sensor information fusion

The prediction model constructed with traffic flow at a certain time can learn the road network congestion state at the corresponding time, and the prediction result represents the future traffic flow under the condition that the road network congestion state does not change. What is to be calculated is the probability of the current true value x in the road network congestion state represented by the two prediction models. Therefore, the true value of the current traffic flow v is used as the target value y, and the predicted values of the two prediction models are respectively used as the expected value.

$$v_j = v_{j-1} \times \delta + (1-\delta)(x_j - x_{i,j})^2 \tag{6}$$

The fuzzy neural network input nodes used for prediction, that is, the number of sensor data required, are not always better. Too much redundant information not only affects the prediction accuracy, but also reduces the efficiency of the algorithm. Therefore, the Taguchi method is introduced in this paper to use sensor data as much as possible under the condition of ensuring certain accuracy, as shown in Fig. 4.

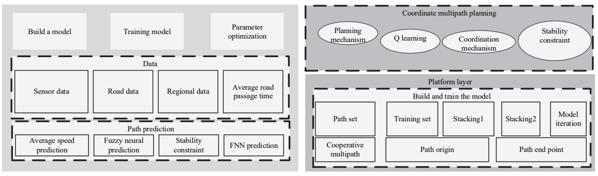

Figure 4 Path planning mechanism design scheme

However, due to the driving level and complex road network environment, even if the vehicles from different starting points and ending points pass through the same section, the time consumed must be different. So the learning process needs constant adjustment. The data generated by the detection vehicle driving from the specified starting point to the specified end point is temporarily valid, and the status of the detection vehicle passing is constantly updated. The final goal is to find the optimal path and time consumption. Assuming that the starting point of the vehicle is k0, the end point is kn, and the time consumption is t0, the learning algorithm is as follows:

Step 1: Observe the operation of all detection vehicles belonging to $i(k_0, t_0)$ and record the historical data of their time spent on each road section.

Step 2: If detecting vehicle reaches gas, jump to Step 3. Or give up.

Step 3: Starting with k_n, reverse check each state and update its Q value, as follows:

(1) If the state is $i(k_0, t_0) = 0$;

(2) If the state is i, k_j is the next state of the detecting vehicle;

(3) The following formula is used to update the learning value:

$$\lambda_i = \arg\min Q(i(k,t), \lambda_i) \tag{7}$$

(4) Click here to find the optimal path, then the optimal time consumption from k_0 to k_n is:

$$J(i(k_0,t_0)) = \min_{\lambda_0 \in \lambda}(i(k_0,t_0), \lambda_0) \tag{8}$$

When the vehicle needs to go out of the warehouse, the first path is a straight line. After reaching a certain point, the vehicle turns to the right to complete the circular path with the minimum turning radius. Considering that the lower right point C of the vehicle may collide with the front left point of the right blocked vehicle when exiting the warehouse, a certain safety distance must be satisfied, that is, the distance between the center of the rear axle of the vehicle and the center $O1$ of the circle should not be less than the distance between the upper left corner of the blocked vehicle and the center $O1$ of the circle. Then:

$$R_{\min} \geq \sqrt{(x_{A1} - x_{O1})^2 + (y_{A1} - y_{O1})^2} \tag{9}$$

At the same time, the distance from the lower left point of the intelligent car to the center of the circle $O1$ should be less than the distance from the upper right corner $B1$ of the left obstacle vehicle to the center of the circle $O1$, namely:

$$R_{\min} \leq \sqrt{(x_{B1} - x_{O1})^2 + (y_{B1} - y_{O1})^2} \tag{10}$$

For safety needs and actual parking space requirements, a safety distance threshold of 0.2 m is set, so the space constraint is:

$$\begin{cases} R_{\min} \geq \sqrt{(x_{A1} - x_{O1})^2 + (y_{A1} - y_{O1})^2} + 0.2 \\ R_{\min} \leq \sqrt{(x_{B1} - x_{O1})^2 + (y_{B1} - y_{O1})^2} + 0.2 \end{cases} \tag{11}$$

4.2 Research on Path Planning Based on Multi-Sensor Data

First, in the initialization process, the initial state node of the random tree is also the only node in the tree. A node is randomly sampled from the unconstrained free space, and the step length is intercepted in the direction of the nearest node and random node traversed in the random tree according to the set distance evaluation function, so that the starting point of this section is near, and it is measured whether this path passes through the obstacle space. If it passes, the new node is eliminated. If not, a new node is added to the random tree space. Finally, the initial node of the random tree is returned, and the path connecting the initial node to the target node is the optimal planning path. The algorithm flow chart is shown in Fig. 5.

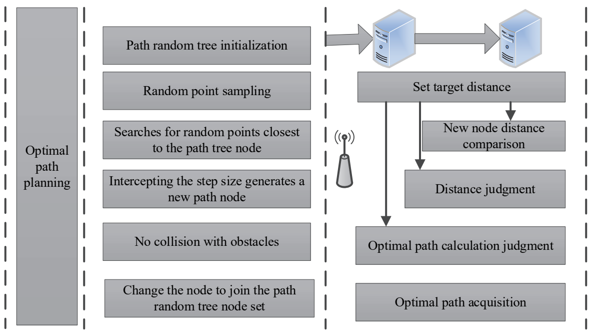

Figure 5 Flowchart of the optimal planning path algorithm

In actual driving, because the width and length of the intelligent car cannot be ignored, it cannot be regarded as a particle for motion processing, otherwise when the intelligent car plans a path close to the obstacle, resulting in a collision between the vehicle and the obstacle, so set a safe distance threshold for smart cars.

Then the safe collision avoidance area of the intelligent car under this node is:

$$(x - x_{\text{new}})^2 + (y - y_{\text{new}})^2 < R_{\min}^2 \tag{12}$$

Given the different effects of different neighborhood agents, when the value iteration process introduces additional information obtained by the neighborhood agents, each agent can ensure that the strategy it makes fully takes into account the strategy of all neighborhood agents. The algorithm is shown in Tab. 3.

Table 3 Multi-agent multipath planning algorithm for sensor collaboration

Step l: According to the reinforcement learning model, initialize the learning rate, Q value table, and establish the feedback matrix r; Step 2: Based on the optimal path planning of Q learning, calculate the Q value table to get the optimal path; Step 3: Using the values proposed in this section, determine whether other Q values except the optimal Q value at each intersection meet the constraint conditions. If yes, it is regarded as the optional optimal path. Some intersections may have only the optimal path, and some intersections may have all intersections. Step 4: Calculate the stability of the corresponding path set. If the given stability constraint is met (such as no less than 0.9), the algorithm ends. Otherwise, skip to Step 3, adjust the change value, and change the path set until the given stability constraint and time constraint are met.

5 SIMULATION

In order to accurately estimate the traffic congestion curve of the sensor in the experimental area, the simulation experiment of no boundary control is carried out first. The traffic demand of the experiment area is realized through the input flow of 8 boundary sections, the specific flow is shown in Tab. 4. In this demand scenario, the road network initially inputs less traffic, and gradually faces traffic congestion for a period of time as the input traffic increases in proportion.

Table 4 Input flow of regional boundary sections

Section number	Simulation time			
	0-950	950-1850	1850-3650	3650-5450
1	950	1850	3650	4850
2	350	650	1250	1650
3	650	1250	2450	3250
4	460	950	1850	2450
5	350	650	1250	1650
6	350	650	1230	1630
7	460	950	1830	2450
8	650	1250	2450	3250

In this experiment, six repeated simulation experiments were conducted based on three control scenarios, and regional travel completion flow, average vehicle speed and average delay were used to evaluate the performance of different control schemes. Table 5 shows the average value of multiple simulation results of the three performance indicators, in which the average speed and average delay are for the whole experiment area, including the border road section. The trip completion flow is the total number of vehicles leaving the experimental area in each simulation interval. Compared with the scenario without boundary control, the travel completion flow and average speed of the proposed method are increased by 44.85% and 18.67% respectively, while the travel completion flow and average speed of the proposed method are increased by 35.8% and 12.6% respectively. Meanwhile, the average delay of the proposed method is reduced by 35.6%. The average delay of the comparison method is reduced by 26.8%. In general, the traffic flow performance of the proposed method is better than that of the comparison method and boundary-free control.

Table 5 Comparative analysis of traffic performance in three simulation control scenarios

Performance index	Borderless control	Comparison method	Textual method	Contrast method improvement	Method improvement in this paper
Trip completion stream	416	572	605	35.8%	44.85%
Average speed / km/h	27.12	30.65	32.51	12.6%	18.67%
Average delay / s/ vehicle	268	197	179	26.8%	35.6%

Fig. 6 shows the variation of boundary flow in the experimental area. It can be clearly seen from the figure that the two boundary control strategies start to work at 25 s, at which time the input flow at the boundary of the region is different. In the scenario without boundary control, the decrease of regional input flow is due to the occurrence of regional traffic congestion, and queue overflow and traffic congestion in the region will also lead to a reasonable reduction of the travel completion flow. In the scenario with comparison method control, the input flow of the boundary input flow decreases significantly after repeated continuous fluctuations, and even approaches the scenario without boundary control for about 30 seconds. The main reason is that the traffic flow on all boundary sections is controlled. In contrast, the method in this paper realizes relatively stable input flow control by introducing dynamic boundary controlled points, which provides more convenient conditions for practical application.

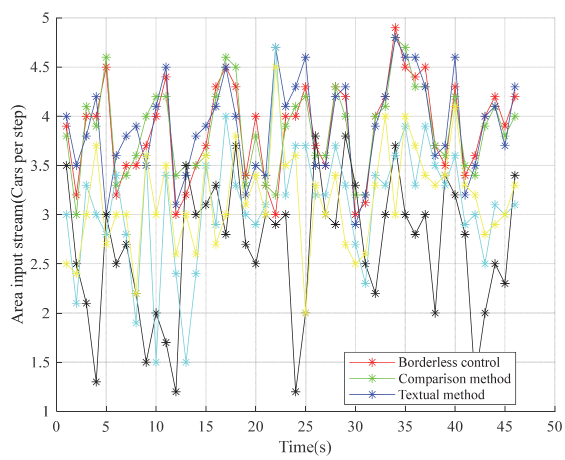

Figure 6 Boundary flow variation diagram of the experimental area

The next step is to train the classifier using historical data, and use the classifier to predict the traffic flow at the target time and determine whether it is a traffic jam. As a contrast, Fig. 7 shows the results of the real current sequence using the clustering method to judge the traffic state, and Fig. 8 shows the results of directly using the classifier to judge the category of the current sequence points without making predictions. Finally, the results of the model in this chapter are shown in Fig. 9, which is the result of predicting the sequence 10 minutes after the current sequence and using the classifier to classify it. These maps also use dotted lines to roughly mark the boundaries of traffic congestion and route planning.

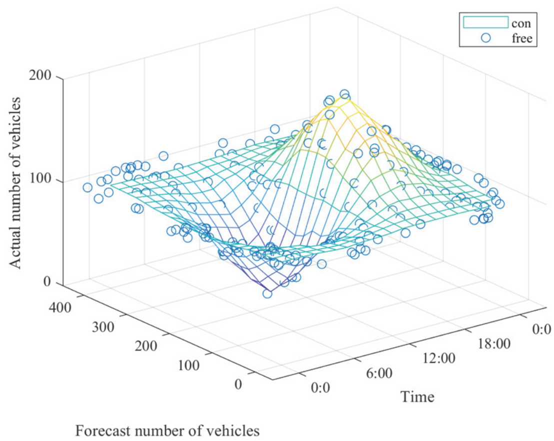

Figure 7 Scatter diagram of intelligent traffic congestion collaboration in real current sequence

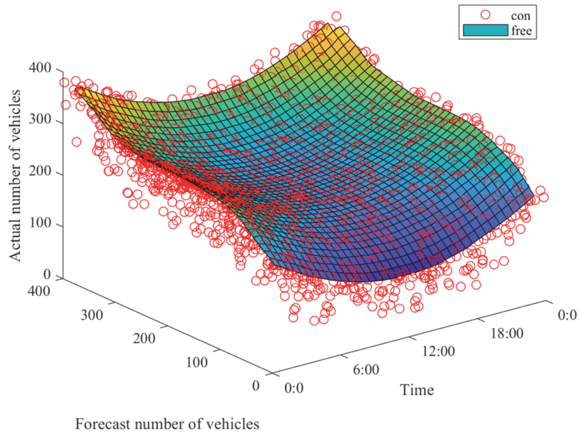

Figure 8 Scatter diagram of the current sequence of intelligent traffic classification

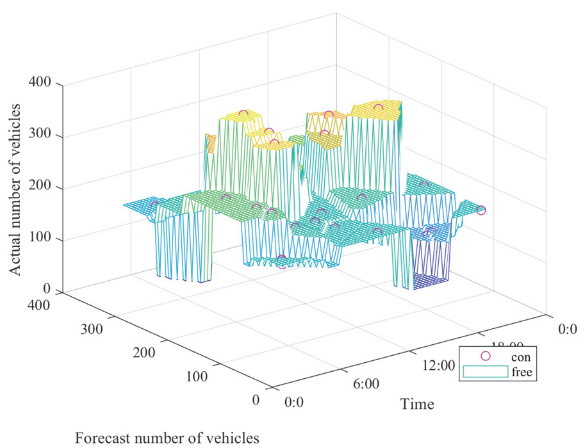

Figure 9 Intelligent traffic path planning diagram of the current sequence

Next, the performance of the last two algorithms for planning time and path set reliability is compared. Fig. 10 shows that the time required for k-shortest planning increases linearly with the network size, while the time required for *Q*-learning multipath planning increases linearly with the number of pairs of the network size. In addition, the reliability of *Q* learning multipath planning is more than 0.9, but the reliability of *k*-shortest planning is difficult to guarantee.

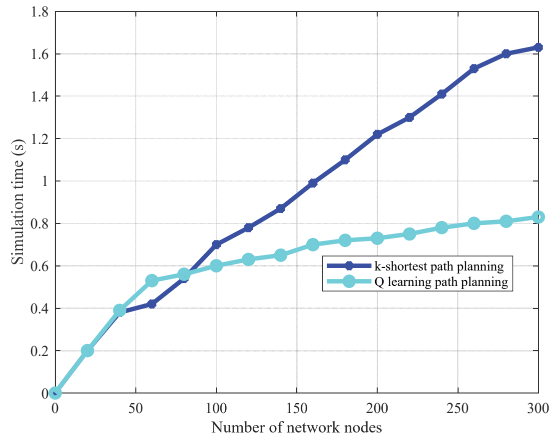

Figure 10 Learning multi-path planning and *k*-shortest planning. The network size increases

In addition, a total of 4 sets of vehicle positioning trajectories and obstacle collision statistics were measured in the experiment for comparison. The whole process of the experimental group of vehicles has the UAV to coordinate traffic congestion location. In the control group, there was no UAV for collaborative traffic congestion positioning in the whole process. The navigation trajectories of vehicles and drones are shown in Fig. 11.

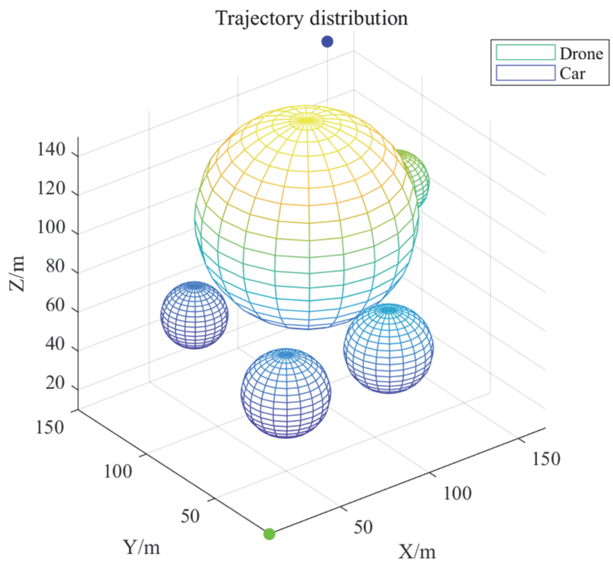

Figure 11 Trajectory distribution of vehicles and UAVs

Fig. 12 shows the comparison of positioning accuracy of different groups with different coordination conditions. As can be seen from Fig. 12, when the vehicle can receive the cooperative signal from UAV C (Uninhabited Air Vehicle Chopper), the accuracy distribution of the experimental group ranges from –1 to 1 m.

Experiments show that the calculation of traffic congestion in collaborative traffic congestion is more accurate, which can reduce the dependence on traffic monitoring sensors. In addition, under the condition that the collaborative network delay meets the requirements, the collaborative traffic congestion system can effectively prejudge the danger, so as to improve the real-time traffic congestion safety of the traffic congestion target.

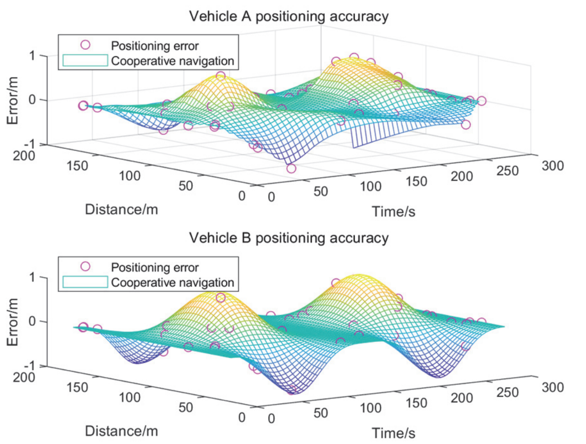

Figure 12 Positioning accuracy of vehicle A and vehicle B under different cooperative conditions

There are many kinds of paths between the two stations. According to the conditions of transportation cost, path length and station capacity, as well as the congestion of one-way and two-way streets and roads, the point-to-point shortest path algorithm in graph theory is used to search, and the result shown in the graph is the best transportation path between the two stations. The calculation results show that, considering the urban traffic network, based on the station capacity information and road condition information collected by the wireless sensor network, the optimal route information can be analyzed and generated. The driver can make the driving route according to the information of the best path. The algorithm has a good role in assisting decision making for vehicle path planning problem while ensuring the quality of solution. It is applicable and easy to popularize.

6 CONCLUSION

In this paper, the application of collaborative traffic congestion information in traffic congestion calculation and risk prediction is modeled and expounded. Compared with the current widely used video surveillance methods, the deployment cost of basic monitoring sensors can be greatly reduced and more accurate calculation results can be obtained. At the same time, hazard prediction based on the sharing of vehicle attributes, location, and speed can reduce the likelihood of collisions or other traffic accidents. In addition, the real-time route planning algorithm of vehicles is given to improve the throughput of urban road network. According to the sensor configuration of traffic road measuring average speed, a fuzzy neural network model of traffic flow prediction is constructed to accurately predict the average speed of each sensor at the next moment, so as to calculate the average passing time of the road at the next moment, and lay a good data foundation for route planning. Dynamic vehicle planning is one of the effective means to solve urban traffic congestion. Using advanced path planning algorithm, the optimal path can be calculated according to the road network condition. The traditional path planning algorithm usually only gives the optimal path, so it is difficult to avoid the problem that there is no alternative path due to accidental paralysis of the road section. In addition, in order to ensure the real-time of route planning, the prediction technology is often used to predict the road network condition in advance. On the premise of ensuring real-time performance, this paper presents a multi-candidate path set with the lowest predictive configuration cost and high stability, and studies the two key technologies of the predictive mechanism, road sensor configuration and multipath planning.

Acknowledgments

The research was supported by the Key scientific research project plan of Henan Higher Education Institutions (24B580003) and Kaifeng science and technology project (2301008). The authors also would like to thank the Dr. Sun Hanzheng's studio, School of Civil Engineering and Transportation Engineering, Yellow River Conservancy Technical Institute.

7 REFERENCES

[1] Lu, Y., Yao, S., & Yao, Y. (2022). Research on the Intelligent Assignment Model of Urban Traffic Planning Based on Optimal Path Optimization Algorithm. *Scientific Programming*, 2022, 1-7. https://doi.org/10.1155/2022/3002923

[2] Yang L. (2021). Optimization Model of Urban Rail Transit Operation Management Based on Neural Network Algorithm. *Journal of Physics Conference Series*, *1982*(1), 12094-12105. https://doi.org/10.1088/1742-6596/1982/1/012094

[3] Lang, H. (2020). Research on Intelligent Prediction of Urban Short-term Traffic Flow Based on Big Data. *Journal of Physics: Conference Series*, *1648*(2), 22074-22079. https://doi.org/10.1088/1742-6596/1648/2/022074

[4] Ruiqi, L., Xian, Z., & Luo, Z. (2018). Research on the intelligent judgment of traffic congestion in intelligent traffic based on pattern recognition technology. *Cluster Computing*, *2018*, 1684-1692. https://doi.org/10.1007/s10586-017-1684-8.

[5] Li, B., Yue, K. Q., & Gan, Z. G. (2021). Multi-UAV Cooperative Autonomous Navigation Based on Multi-agent Deep Deterministic Policy Gradient. *Yuhang Xuebao/Journal of Astronautics*, *42*(6), 757-765. https://doi.org/10.3873/j.issn.1000-1328.2021.06.009

[6] Domingo, M. C. (2021). Power Allocation and Energy Cooperation for UAV-Enabled MmWave Networks: A Multi-Agent Deep Reinforcement Learning Approach. *Sensors (Basel, Switzerland)*, *22*(1), 73-84. https://doi.org/10.3390/s22010270

[7] Min, W., Jinghui, G., & Wang, W. (2019). Smart Grid Network Resource Scheduling Algorithm Based on Network Calculus. *Integrated Ferroelectrics*, *199*, 1-11. https://doi.org/10.1080/10584587.2019.1592592

[8] Yeckehzaare, I., Chen, S. S., & Barghi, T. (2023). Reducing Procrastination Without Sacrificing Students' Autonomy Through Optional Weekly Presentations of Student-Generated Content. *Proceedings of the 54th ACM Technical Symposium on Computer Science Education V. 1*, *23*(Dec.1), 284-296. https://doi.org/10.1145/3545945.3569839

[9] Su, Z., Liu, Q., & Gong, L. (2023). Energy Consumption Optimization of Connected and Autonomous Vehicles Based on Cooperative Perception in Ramp Overflow Scene.

Journal of Circuits, Systems and Computers, *32*(16), 2821-2835. https://doi.org/10.1142/S0218126623502821

[10] Meng, X. & Li, X. (2020). Research on Optimization of Port Logistics Distribution Path Planning Based on Intelligent Group Classification Algorithm. *Journal of Coastal Research*, *115*(sp1), 205-223. https://doi.org/10.2112/JCR-SI115-064.1

[11] Ouyang, F. (2020). Research on Port Logistics Distribution Route Planning Based on Artificial Fish Swarm Algorithm. *Journal of Coastal Research*, *115*(sp1), 78-87. https://doi.org/10.2112/JCR-SI115-023.1

[12] Wu, L., Guo, S., & Han, L. (2023). Autonomous detection of myocarditis based on the fusion of improved quantum genetic algorithm and adaptive differential evolution optimization back propagation neural network. *Health Information Science and Systems*, 11(1), 39-58. https://doi.org/10.1007/s13755-023-00237-8

[13] Xu, T., Wang, T., & Ye, C. (2023). Research of Electric Cable Path Planning Based on Heuristic Optimization Algorithm in Mixed-Land Scenario. *Energy Industry*, *120*(11), 2629-2650. https://doi.org/10.32604/ee.2023.027537

[14] Du, L. Z., Ke, S., & Wang, Z. (2019). Research on multi-load AGV path planning of weaving workshop based on time priority. *Mathematical biosciences and engineering: MBE*, *16*(4), 2277-2292. https://doi.org/10.3934/mbe.2019113

[15] Zhou, J. Q. (2020). Research on Path Planning Based on Improved Fuzzy Intelligent Algorithm. *Computer Science and Application*, *10*(5), 1044-1050. https://doi.org/10.12677/CSA.2020.105108

[16] Jiang, K., Su, D., & Zheng, Y. (2019). Intelligent acquisition model of traffic congestion information in the vehicle networking environment based on multi-sensor fusion. *International Journal of Vehicle Information and Communication Systems*, *4*(2), 155-168. https://doi.org/10.1504/IJVICS.2019.101512

[17] Zheng, X., Huang, B., & Ni, D. (2018). A novel intelligent vehicle risk assessment method combined with multi-sensor fusion in dense traffic environment. *Journal of Intelligent and Connected Vehicles*, 7(1), 187-196. https://doi.org/10.1108/JICV-02-2018-0004

[18] Yan, Z., Yanran, L., & Chung-Ming, O. (2018). Real-time predication and navigation on traffic congestion model with equilibrium Markov chain. *International Journal of Distributed Sensor Networks*, *14*(4), 6978-6989. https://doi.org/10.1177/1550147718769784

[19] Ruiqi, L., Xian, Z., & Luo, Z. (2019). Research on the intelligent judgment of traffic congestion in intelligent traffic based on pattern recognition technology. *Cluster Computing*, *2019*(5), 1684-1692. https://doi.org/10.1007/s10586-017-1684-8

[20] Pan, Q. & Zhang, H. (2019). Key Algorithms of Video Target Detection and Recognition in Intelligent Transportation Systems. *International Journal of Pattern Recognition and Artificial Intelligence*, *2019*(4), 162-178. https://doi.org/10.1142/S0218001420550162

[21] Ji, Y. & Liu, B. (2022). Research and Implementation of Robot Path Planning Based on Ant Colony Algorithm. *Journal of Physics: Conference Series*, *2171*(1), 12074-12089. https://doi.org/10.1016/j.eswa.2013.09.018

[22] Wang, K., Peng, H., & Zhao, M. (2021). Collaborative exploration of multiple unmanned surface vessels in complex areas based on PPO algorithm. *Journal of Physics: Conference Series*, *2003*(1), 12017-12029. https://doi.org/10.1088/1742-6596/2003/1/012017

[23] Li, Y. (2020). Research on Information Capacity Prediction of Mobile Sensing Platform in Internet of Things Based on Collaborative Congestion. *International Journal of Autonomous and Adaptive Communications Systems*, *13*(3), 12-23. https://doi.org/10.1504/IJAACS.2020.10031737

[24] Guo, H. & Liu, J. (2018). Collaborative Computation Offloading for Multiaccess Edge Computing Over Fiber-Wireless Networks. *IEEE Transactions on Vehicular Technology*, 67(5), 421-456. https://doi.org/10.1109/TVT.2018.2790421

[25] Toutouh, J. & Alba, E. (2018). A Swarm Algorithm for Collaborative Traffic in Vehicular Networks. *Vehicular Communications*, *2018*, 127-137. https://doi.org/10.1016/j.vehcom.2018.04.003

[26] Dawei, S., Wei, Y., & Yuhuai, P. (2018). Congestion Control and Traffic Scheduling for Collaborative Crowdsourcing in SDN Enabled Mobile Wireless Networks. *Wireless Communications & Mobile Computing*, *2018*, 31-41. https://doi.org/10.1155/2018/9821946

[27] Hu, W., Dong, J., & Yang, K. (2023). Network planning of metro-based underground logistics system against mixed uncertainties: A multi-objective cooperative co-evolutionary optimization approach. *Expert Systems with Applications, 217*, 119554-119565. https://doi.org/10.1016/j.tranpol.2021.10.020

[28] Peng, G., Jia, T., & Kuang, H. (2022). Energy consumption in a new lattice hydrodynamic model based on the delayed effect of collaborative information transmission under V2X environment. *Physica A: Statistical Mechanics and its Applications*, 585-597. https://doi.org/10.1016/j.physa.2021.126443

Contact information:

Hanzheng SUN
(Corresponding author)
School of Civil Engineering and Transportation Engineering,
Yellow River Conservancy Technical Institute,
Kaifeng, 475004, China
E-mail: Dorsun0326@163.com

Xuejing ZHANG
School of Water Conservancy Engineering,
Yellow River Conservancy Technical Institute,
Kaifeng, 475004, China

Dan LI
School of Civil Engineering and Transportation Engineering,
Yellow River Conservancy Technical Institute,
Kaifeng, 475004, China

Jianling TAN
School of Water Conservancy Engineering,
Yellow River Conservancy Technical Institute,
Kaifeng, 475004, China