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A risk identification method of road traffic operation safety considering traffic conflict

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Abstract

Road traffic operation safety is an important part of the road traffic system, and is also one of the topics of great concern in the world. Road traffic safety management has been highly valued by all countries in the world, and road traffic safety evaluation as road traffic safety management is particularly important. This paper proposes a road traffic operation risk identification method considering traffic conflict. Firstly, traffic conflict mechanism is analyzed, and the distance collision time, the time after occupation and the anti-collision deceleration are determined as traffic conflict indicators; Then, the traffic conflict frequency prediction model is built according to the traffic conflict indicators; Finally, according to the traffic conflict rate of the prediction model, the maximum membership method is used to identify the risk of road traffic operation safety, estimate the probability of risk occurrence, divide the risk level. The simulation results show that the method has better accuracy and shorter identification time for road traffic operation safety risk identification

Keyword - traffic conflict, road traffic, operation safety, risk identification

1. Introduction

Road traffic safety refers to the state in which personal injury or property loss can be controlled at an acceptable level in the process of traffic activities. Traffic safety means that the possibility of loss of people or things is acceptable; If this possibility exceeds the acceptable level, it is unsafe. As a dynamic and open system, the safety of road traffic system is not only restricted by the internal factors of the system, but also affected by the external environment of the system, and is closely related to factors such as people, vehicles and road environment. The unreliable, unbalanced and unstable of any factor in the system may lead to conflicts and contradictions, resulting in unsafe factors or unsafe conditions.

With the rapid development of economy, there are more and more vehicles on the road, and the traffic congestion has increased significantly. Due to the large number of openings in urban roads and the large gradient of local roads, the road system includes trunk roads and secondary trunk roads, and the types and sizes of signal-controlled openings and non-signal controlled openings are different. Some nodes are complex, and the separation and merging phenomenon is serious. There is a mismatch between the number of lanes in the basic section and the node area, causing traffic congestion in the bottleneck section, thus causing traffic conflicts [3, 8]. It makes it easier for drivers to have abnormal driving behaviors such as rapid acceleration and deceleration, thus increasing the safety risk of traffic operation. In order to avoid the safety risk of traffic operation in advance, reduce the occurrence of traffic accidents, and improve the safety of road traffic operation, it is particularly important to identify the safety risk of traffic operation on the accident-prone roads such as curves [7].

Zhang et al. [14] proposes a method of urban road traffic safety risk identification based on driving behavior data, obtains the abnormal driving behavior of urban road traffic, carries out qualitative analysis of the relationship between this behavior and different road conditions, and builds a correlation model between the two according to the analysis results, so as to identify urban road traffic safety risks. Yang et al. [13] proposes a road traffic operation safety risk identification method based on the WOMDI-Apriori algorithm. Under the time and space dimensions, traffic accident data is collected through the traffic big data platform, and the weight of traffic accident data is calculated by combining the analytic hierarchy process and grey correlation degree. According to the calculation results, the WOMDI-Apriori algorithm is used to mine traffic accident data association rules from the perspective of accident cause and accident dimension autocorrelation, Based on the mining results, identify the safety risks of road traffic operation. However, the accuracy of the above two methods for road traffic operation safety risk identification is low, resulting in poor identification effect. Yang et al. [11] proposes a road traffic operation safety risk identification method based on the N-K model, analyzes the road traffic operation safety risk factors, and constructs a factor coupling risk model based on the risk factors through the N-K model to obtain the coupling risk value, thus completing the road traffic operation safety risk identification. Sun et al. [6] proposes a real-time identification method of dangerous traffic flow state based on support vector machine model, analyzes the characteristics of traffic flow, extracts the precursor features of traffic accidents, and uses correlation selection algorithm to pre-process the extracted features. According to the pre-processing results, the dangerous traffic flow state is classified by support vector machine model to identify the safety risks of traffic operation. However, the above two methods take a long time to identify traffic operation safety risks, resulting in low identification efficiency. Aiming at the short time and low accuracy of road traffic operation safety risk identification, this paper studies the road traffic operation safety risk identification method considering traffic conflict.

2. Risk identification method for road traffic operation safety

2.1. Analysis of traffic conflict mechanism

(1) Classification of traffic conflicts

Traffic conflict is to determine the potential safety risks in the process of road traffic operation by selecting appropriate measurement indicators. It is an effective means to analyze the safety problems of road traffic operation. The traffic conflict is judged by the distribution of vehicles in time and space. When two vehicles are approaching in a certain time and space distribution, if the driver does not take measures, a collision will occur, which can be defined as a traffic conflict [1]. Due to the complexity of the traffic flow system in the actual road traffic operation process, the types of traffic conflicts generated are also different. In the process of following, the tracks of the two vehicles are on the same axis, so the possibility of rear-end collision is greater. When the vehicles change lanes or turn, the side collision between vehicles is more likely to occur in the two-dimensional plane. In order to reasonably classify the types of traffic conflicts, refer to the perspective analysis of highway vehicle collisions, and take the conflict classification method of SSAM (Surrogate Safety Assessment Model) micro-conflict identification software developed by the Federal Highway Administration as the benchmark [9]. The type of conflict is divided according to the potential collision angle between vehicles. Because the road traffic flow is one-way, rear-end conflict and lateral conflict may occur between vehicles. With the longitudinal centerline of the conflicting vehicle as the axis, rear-end conflict is defined when the angle between the two vehicles is less than or equal to 15 °, while the conflicting traffic is defined as lateral conflict when the angle is between 15 ° and 85 °.

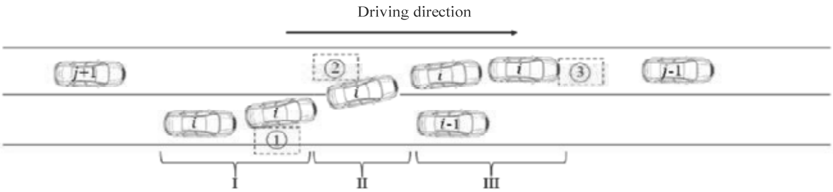

Fig. 1 - Schematic diagram of vehicle lane change process

(2) Analysis of the formation process of traffic conflict

In the process of car-following, vehicles in the same lane are prone to rear-end collision due to the fast speed of traffic flow. When the distance between the current guide car and the car-following car is too small and the speed of the car-following car is greater than that of the leading car, or when the leading car has emergency braking and other behaviors due to other factors, the rear-end collision will occur between the vehicles. At this time, the driver is required to take risk avoidance actions in a short time to avoid the traffic conflict from turning into vehicle collision. If the risk avoidance is successful, the vehicle will continue to run normally, Failure to avoid risks will cause rear-end collision to turn into rear-end collision [2]. The types of conflicts generated in the lane change behavior of road traffic are different according to the state of the vehicle. Especially in the process of lane change and overtaking, the vehicle needs to increase its running speed in a short time to complete the overtaking behavior. The analysis of conflict during lane change is shown in Figure 1. The lane change process can be divided into the forward - offset phase I of the original lane, the cross-lane offset phase II and the target lane offset - return phase III. In the figure, vehicle i is the lane change vehicle, vehicle $i-1$ is the vehicle in front of the original lane, vehicle $j+1$ is the vehicle behind the target lane, and vehicle $j-1$ is the vehicle in front of the target lane.

In the first stage of the lane change process, the driver needs to observe the traffic flow of the target lane, and at the same time start to accelerate and shift to the target lane. At this time, the vehicle is still in the original lane, and the increase of speed may cause the lane change vehicle to collide with the vehicle $i-1$ in front of the original lane in the red area □; In the second stage, the vehicle is in the state of cross-lane body offset, and there is a longitudinal overlap area between the vehicle body and the vehicle behind the target lane, so in the red area □ the target vehicle may have a lateral conflict with vehicle $j+1$; In the third stage, the vehicle fully enters the target lane, the driver adjusts the direction to go straight, and is in the red area □ where there may be rear-end collision with vehicle $j-1$.

2.2. Traffic conflict indicator acquisition

2.2.1. Indicator selection principle

The determination of traffic conflict indicators is one of the core links of this research. Whether the selected indicators are comprehensive and scientific will directly affect the final effect of road traffic operation safety risk identification. Therefore, the selection of indicators should follow the following basic principles:

(1) Principle of comprehensiveness

There are many factors affecting traffic conflict. When identifying the risk of road traffic operation safety, all aspects of risk factors should be considered. Compared with ordinary daily activities, the road traffic system includes traffic control, traffic management, traffic policy and other factors, which should be taken into account when analyzing traffic conflict events. Therefore, road traffic operation safety risk identification requires more comprehensiveness.

(2) Guiding principle

The selected traffic conflict indicators must be able to point to the research objectives. The 'traffic conflict' in this paper refers to any uncertain factors that make the road traffic operation deviate from the expected goal, affect the road traffic operation, cause traffic hazards, and affect the quality of road traffic operation service in the process of road traffic operation. Traffic conflict indicators must reflect the impact on the safety, punctuality and reliability of its traffic operation.

(3) Scientific principle

Scientificity is the principle for the construction of any indicator system. The scientific selection of traffic conflict indicators can affect the rationality of the results of risk indicators. Therefore, the selection of indicators should be based on scientific basis and strive to scientifically and accurately reflect the impact on road traffic operation objectives. The scientific basis of this study mainly includes relevant national standards and specifications, relevant planning documents and emergency plans of road traffic in the past, existing literature and comprehensive opinions of authoritative experts.

(4) Principle of representativeness

There are many factors that affect the identification results, and if all of them are considered, it may cause repeated workload. For example, traffic flow, vehicle speed and vehicle density are all factors that belong to the traffic flow environment. There is a great correlation between them. The third volume can be calculated from any two of them. If these three factors are included in the traffic conflict indicator system, it will increase the repeated workload. Therefore, on the basis of not affecting the credibility of the results, the risk factors of attribute redundancy should be removed from many factors, which can improve the identification efficiency without affecting the credibility of the identification results.

(5) Principle of practicality

The traffic conflict indicator system should be operable, collectable and quantifiable. Among many influencing factors, some factors are easy to characterize or quantify, for example, whether there are obstacles on the road, there are only 'yes' or 'no' possibilities, and this information is easy to obtain; Some factors are relatively abstract and difficult to quantify, such as the psychological state of motor vehicle drivers. In the selection of traffic conflict indicators, in order to facilitate data acquisition and research, priority should be given to quantitative indicators.

2.2.2. Indicator selection

Under the analysis of traffic conflict mechanism, traffic conflict indicators are selected according to the principle of indicator selection. In this paper, video recording method is used to obtain traffic flow and traffic conflict data, and three indicators of distance collision time, post-occupation time and collision avoidance deceleration are selected to judge road traffic conflict [12, 4, 10].

(1) Time To Collision (TTC)

The distance collision time (TTC) index is one of the commonly used indexes in the conflict calculation models at home and abroad. At a certain moment, if the drivers of the two vehicles do not take any adjustment measures and let the vehicle continue to drive at the current speed and direction, there will inevitably be a collision. The time difference between the conflict and the accident without any operation behavior is recorded as the distance collision time. It is not difficult to see that when the distance from the collision is short, the driver has a high probability of not being able to make timely and effective avoidance actions, so the collision risk is high. The TTC index takes time as a measure and takes into account the spatial relationship between the two vehicles, so it has been widely used in the research of rear-end collision analysis at home and abroad, and has achieved fruitful research results.

Assuming that the car-following vehicle has a higher speed and the positive direction of the x-axis is the driving direction of the vehicle, the centroid treatment is usually used for the vehicle in the previous macro traffic flow analysis, but the length of the vehicle body must be taken into account when analyzing the rear-end collision, especially the large vehicles in the road traffic flow account for a certain proportion, and the body length has a more significant impact on the determination of the rear-end collision. In summary, the TTC index in the car-following process is calculated as follows:

$$\mathrm{TTC_i(t)} = \frac{\mathrm{x_{i-1}(t)+x_i(t)-L_{i-1}}}{\mathrm{V_i(t)-V_{i-1}(t)}} \tag{1}$$

where $\mathrm{TTC_i(t)}$ represents the distance and collision time of vehicle i rear-end collision with vehicle $\mathrm{i-1}$ (i.e. the front vehicle), $\mathrm{x_{i-1}(t)}$ represents the position of vehicle $\mathrm{i-1}$ on the coordinate axis at time t, $\mathrm{x_i(t)}$ represents the position of vehicle i on the coordinate axis at time t, $\mathrm{V_{i-1}(t)}$ represents the speed of vehicle $\mathrm{i-1}$ at time t, $\mathrm{V_i(t)}$ represents the speed of vehicle i at time t, and $\mathrm{L_{i-1}}$ represents the body length of vehicle $\mathrm{i-1}$.

(2) Post Encroachment Time (PET)

Compared with TTC indicator, PET indicator is easier to apply in traffic conflict identification. It is only necessary to record the time of front and rear vehicles arriving at the section based on a certain section. Set the time of i vehicle arriving at the designated section as $\mathrm{T_i}$, and the time of $\mathrm{i-1}$ vehicle arriving at the designated section as $\mathrm{T_{i-1}}$, then:

$$\mathrm{PET_i = T_i - T_{i-1}} \tag{2}$$

The calculation method of PET index is simple, and only takes time as the measure of conflict risk. It requires less variables to be obtained, and can be obtained directly from video data. It has high flexibility in practical application, and can also be applied to lateral conflict of track intersection.

(3) Deceleration Rate to Avoid Crash (DRAC)

The DRAC indicator is widely used in the study of rear-end collision. This indicator takes the vehicle speed difference and deceleration assumption as the main measure of conflict determination. The definition of DRAC indicator in rear-end collision can be understood as: when the speed of the following car on the same lane is greater than the speed of the leading car, the deceleration required by the following car to avoid rear-end collision through braking is the DRAC indicator. This indicator significantly reflects the impact of speed difference and acceleration on the safety of road traffic operation. At the same time, the braking conditions coupled with vehicle and road conditions are considered. When the deceleration to avoid collision exceeds the maximum deceleration of the vehicle under the current road conditions, it can be determined [5]. The calculation formula of the index is as follows:

$$\mathrm{DRAC_i} = \frac{\mathrm{V_i(t)-V_{i-1}(t)}}{\Delta \mathrm{t}} \tag{3}$$

where $\mathrm{DRAC_i}$ represents the maximum deceleration of vehicle i to avoid collision, and $\Delta\mathrm{t}$ represents the time difference between the two vehicles.

DRAC indicators have great similarities with TTC indicators in terms of risk measurement. TTC indicators mainly rely on speed and distance and take time as the measurement indicator, while DRAC indicators further consider the deceleration characteristics related to vehicle braking performance and road conditions.

2.3. Traffic conflict indicator data preprocessing

Since the traffic conflict indicators obtained above are missing and abnormal, and there is noise, it is necessary to preprocess the traffic conflict indicator data obtained above.

(1) Missing data filling

When collecting data, the data is missing due to the data transmission failure at some time. There are two main situations: one is that the data value of a certain attribute at a certain time is missing; The second is that the time of data sampling is discontinuous, and the data of all fields are missing at a certain time. Therefore, the weighted average method is used to fill in the missing data, and the expression is:

$$x_i = \frac{ax_{i-2}+bx_{i-1}+bx_{i+1}+ax_{i+2}}{k} \quad (4)$$

where x_i represents missing data, $x_{i-2}, x_{i-1}, x_{i+1}, x_{i+2}$ represents normal data for 2s before and after missing data, a, b represents the weight of missing data, and k represents the time.

(2) Outlier elimination

Abnormal data refers to the data with large differences between some data and other data due to data acquisition equipment and other reasons. If not processed, it will not accurately reflect the characteristics of traffic operation changes, and will affect the identification accuracy of road traffic operation safety risks below. Therefore, this paper adopts the Laida criterion applicable to large sample data (3 σ Criteria) to handle outliers:

$$|x_k - \overline{x}| > 3\sigma \quad (5)$$

where x_k represents the data at k time, $\overline{x}$ represents the arithmetic mean of $x_1, x_2, \ldots, x_n$, and σ represents the standard deviation.

(3) Data denoising

In the process of collecting traffic conflict data, affected by the external environment, the collected data has noise. In order to ensure the data quality, this paper uses wavelet threshold denoising method to denoise the traffic conflict indicator data.

A one-dimensional data model with noise can be expressed as:

$$f_t = s_t + n_t \quad (6)$$

where f_t represents noisy data, s_t represents raw data, and n_t represents Gaussian white noise.

Usually, the appropriate wavelet basis function is selected to perform discrete wavelet transform on f_t, and then the wavelet transform coefficients containing the real data and noise data in the original data are obtained. Where, the decomposed low frequency part is A_1 and the high frequency part is D_1, D_2, D_3, then the noise data after decomposition is:

$$S = A_1 + D_1 + D_2 + D_3 \quad (7)$$

For high-frequency decomposition coefficients less than the threshold value, the data corresponding to these coefficients are considered as noise data, and these data are rounded off; For high-frequency decomposition coefficients greater than the threshold, it is considered that the corresponding variables of these coefficients are caused by real data, and these coefficients are processed according to certain rules. This paper uses heuristic threshold denoising algorithm to complete:

Step 1: Wavelet decomposition, select appropriate wavelet base to decompose signal j layer by layer.

Step 2: Select the threshold to process the coefficients obtained after wavelet decomposition.

Step 3: Signal reconstruction, which is based on the N-level coefficients of wavelet decomposition and the high-frequency coefficients from the first level to the j-level after threshold processing. Through the decomposition and reconstruction of wavelet, the traffic conflict indicator data can be de-noised.

2.4. Traffic operation safety risk identification based on traffic conflict

The traffic conflict rate represents the proportion of the number of traffic conflicts in the road traffic flow. The number of traffic conflicts reflects the safety level of the traffic conflict area to a certain extent. The higher the number of traffic conflicts, the worse the traffic safety situation. Therefore, according to the traffic conflict index data after the above pretreatment, a traffic conflict frequency prediction model is built to obtain the traffic conflict rate, calculate the probability of occurrence of road traffic operation safety risk, and divide the risk level to identify the road traffic operation safety risk.

The purpose of establishing the traffic conflict frequency prediction model is to predict the traffic conflict frequency of the road section in a certain period of time by using the factors that have a prominent impact on the occurrence of the conflict, such as the traffic flow of the road section, the road linearity and the traffic environment. The frequency of traffic conflict is predicted by building a negative binomial model of random effects. The prediction model of traffic conflict frequency in this paper is:

$$P(X = u_{it}) = \exp(\beta_0 + \beta * x_{it} + \varepsilon_{it}) \tag{8}$$

where $P(X = u_{it})$ represents the probability of k accidents in section i at time t, u_{it} represents the expected value of traffic conflict in section i at time t, β_0 represents the intercept term, β represents the vector of the parameters to be estimated, x_{it} represents the explanatory variable, and ε_{it} represents the error term.

When a driver encounters a traffic conflict, the ineffective avoidance will cause a traffic accident. From the perspective of the severity of the traffic conflict, the more serious the traffic conflict is, the higher the correlation between the traffic conflict and the road traffic accident is. Therefore, this paper calculates the traffic conflict rate. Therefore, the traffic conflict rate is calculated according to the prediction model built above.

Set the conflict threshold. If the running state of the vehicle is within the threshold range, the vehicle has a traffic conflict, and each vehicle has a traffic conflict in any confluence zone, the vehicle is deemed to be a traffic conflict vehicle. Then the conflict rate under different conflict thresholds can be calculated. The conflict rate calculation formula is as follows:

$$W_s = \frac{N}{Q * L} \tag{9}$$

where W_s represents the conflict rate of the section, N represents the number of conflicts per unit time, L represents the length of the data collection section, and Q represents the average hourly traffic volume of each section.

According to the conflict rate obtained above, the risk identification of road traffic operation safety is carried out and the probability of risk occurrence is estimated. The specific steps are as follows:

(1) Define and describe five fuzzy subsets of the possibility of various risk factors, that is, basically impossible, less likely, possible, more likely, and very likely. Determine the membership of various risk factors to these five fuzzy subsets through voting, and obtain the fuzzy relationship matrix R.

$$R = \begin{bmatrix} r_{11} r_{12} \cdots r_{15} \\ r_{11} r_{11} \cdots r_{25} \\ \vdots \quad \vdots \quad \ddots \quad \vdots \\ r_{N1} r_{N2} \cdots r_{N5} \end{bmatrix} \tag{10}$$

where, r_{ij} refers to the membership of the i road traffic safety risk factors to the j fuzzy subset, and N refers to the number of risk factors.

(2) According to the above fuzzy relation matrix, the fuzzy comprehensive evaluation result vector B of the occurrence probability of road traffic operation safety risk is obtained.

Tab. 1 - Risk classification of road traffic operation safety

Hazard level	Conflict severity	Time intensity range of traffic conflict	Judgment of close intersection
I	good	M≤3.8	no
II	light	3.8＜M≤5.5	no
III	moderate	5.5＜M≤8.3	yes
IV	serious	8.3＜M	yes

$$B = W * R = (w_1, w_2, \ldots, w_N)\begin{bmatrix} r_{11} r_{12} \cdots r_{15} \\ r_{11} r_{11} \cdots r_{25} \\ \vdots \quad \vdots \quad \ddots \quad \vdots \\ r_{N1} r_{N2} \cdots r_{N5} \end{bmatrix} = (b_1, b_2, b_3, b_4, b_5) \tag{11}$$

where b_i represents the degree of membership of the road traffic operation safety risk to the fuzzy subset of grade i, and W represents the weight vector.

(3) According to the evaluation results, the membership degree of five fuzzy subsets is calculated by using the maximum membership degree method to perform the inverse fuzzy operation, and the probability of occurrence of road traffic operation safety risk L is obtained:

$$L = \begin{cases} 90\% & b_1 = \max(b_1, b_2, b_3, b_4, b_5) \\ 70\% & b_2 = \max(b_1, b_2, b_3, b_4, b_5) \\ 50\% & b_3 = \max(b_1, b_2, b_3, b_4, b_5) \\ 30\% & b_4 = \max(b_1, b_2, b_3, b_4, b_5) \\ 10\% & b_5 = \max(b_1, b_2, b_3, b_4, b_5) \end{cases} \tag{12}$$

According to the calculated probability of occurrence of road traffic operation safety risk, combined with the conflict threshold judgment, the road traffic operation safety risk level is divided, as shown in Table 1. The corresponding hazard levels are described as follows:

Class I: the traffic operation is in good order, the design of adjacent intersections is reasonable, and it is not a close intersection; The driver drives easily, passes without psychological pressure, and feels very safe; The degree of traffic conflict is relatively light, and there is almost no interference between traffic flows, which indicates that the road traffic is safe.

Class II: the traffic operation order is acceptable, and the design of adjacent intersections is relatively reasonable, which is not a close intersection; The driver drives more easily, has less traffic pressure and feels safer; The degree of traffic conflict is acceptable, and the mutual interference of traffic flow is relatively light, indicating that the road traffic operation is relatively safe.

Class III: the traffic operation order is deteriorated, and the geometric characteristics of adjacent intersections are problematic, which belongs to the close intersection; Drivers need to pay attention to driving. The traffic pressure is high and the driving pressure is acceptable; The degree of traffic conflict is a bit serious, and the mutual interference of traffic flow is acceptable, which indicates that there are risks in road traffic operation safety.

Class IV: the traffic operation is in disorder, and the geometric characteristics of adjacent intersections have major problems, which belongs to the close intersection; The driver needs to be careful when driving. The traffic pressure is high and the driving pressure is high; The degree of traffic conflict is serious and the mutual interference of traffic flow is large, which indicates that the safety risk of road traffic operation is high.

When the time intensity of traffic conflict is greater than 5.5 times/(vehicle • hour), the traffic conflict at the adjacent intersection is moderate or more serious, and it is determined as a close intersection. It is necessary to optimize and transform it.

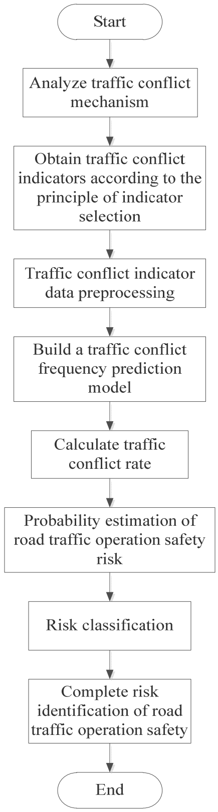

Fig. 2 - Specific flow chart of this method

After optimization and transformation, it can improve its driving safety and improve its driving efficiency. When the time intensity of traffic conflict is less than or equal to 5.5 times/(vehicle • hour), the traffic conflict at the adjacent intersection is light or in good condition, then it is not a close intersection. Even if the distance between them is short, the traffic flow may not be large, which will not affect the overall operation, or its traffic flow is large, but its lane change ratio and conflict rate are very small, so it is not necessary to reform it.

To sum up, the specific flow of the road traffic operation safety risk identification method considering traffic conflict proposed in this paper is shown in Figure 2.

3. Simulation experiment analysis

In order to verify the effectiveness of the road traffic operation safety risk identification method considering traffic conflict proposed in this paper in practical application, the accuracy and time of road traffic operation safety risk identification are taken as experimental indicators, and the reference [11] method and reference [6] method are selected as comparison methods, and the experimental test is carried out with this method. The video recording method is used to obtain the road traffic accident information, and the accident information is shown in Table 2. Obtain road traffic data through data collection, and mark the occurrence of accidents as '1' and the absence of accidents as '0'. Some data are shown in Table 3.

Tab. 2 - Accident information

	road number	G42
Accident location information	Road name	Shanghai Nanjing Expressway
	Station	K156+00-K283+90
	Road direction	Small station - large station (along the direction)
		Large Station - Small Station (Reverse)
Accident time information	Date of accident	2021.01.01-2022.12.31
	Accident time	00:00-23:59
Accident status information	Description of accident form	-
	Description of accident severity	Minor, ordinary, major and extra large
	Number of fatalities	N (set of natural numbers)
	Number of accident injuries	N (set of natural numbers)
	Types of vehicles involved in the accident	-
	Accident weather	-
	Brief description of the accident	-

Tab. 3 - Road traffic data

Traffic volume (vehicle/5min)	Average speed of passenger car (km/h)	Average speed of freight car (km/h)	Percentage of car following (%)	Average headway (m)	Time share (%)	cause the accident
192	64	63	56	109	5	0
118	48	25	37	21	2	1
186	54	70	57	176	3	1
199	84	58	64	149	3	0
293	68	72	95	93	14	1
500	66	71	84	105	13	0
126	68	38	44	444	4	1
73	68	25	30	404	1	0

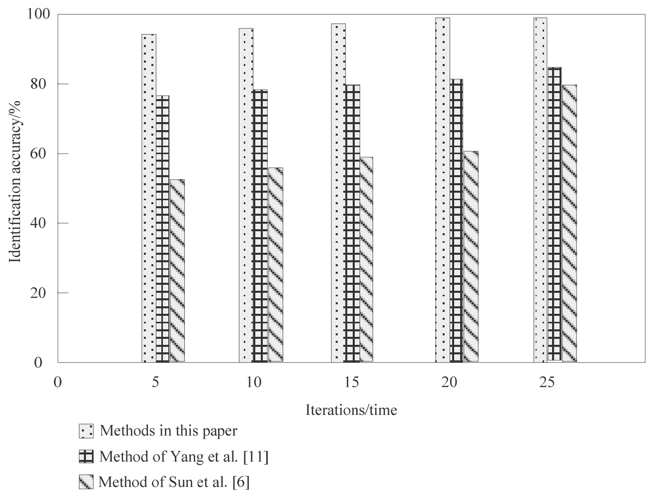

Fig. 3 - Comparison results of road traffic operation safety risk identification accuracy of three methods

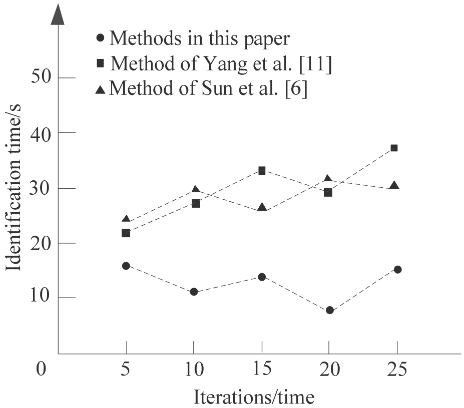

Fig. 4 - Comparison results of road traffic operation safety risk identification time of three methods

The method in this paper, method of Yang et al. [11] and Sun et al. [6] are used to identify the road traffic operation safety risks and test the identification accuracy of the three methods. The test results are shown in Figure 3. According to Figure 3, the accuracy of road traffic operation safety risk identification of the method in this paper can reach up to 98%, the accuracy of road traffic operation safety risk identification of Yang et al. [11] can reach up to 84%, the accuracy of road traffic operation safety risk identification of Sun et al. [6] can reach up to 78%, the accuracy of road traffic operation safety risk identification of the method in this paper is the highest, and the identification effect is the best.

The method in this paper, the method of Yang et al. [11] Sun et al. [6] are used to compare the time used for road traffic operation safety risk identification. The comparison results are shown in Figure 4. According to Figure 4, the method in this paper takes less than 18s to identify the road traffic operation safety risk, Yang et al. [11] takes less than 40s to identify the road traffic operation safety risk, and Sun et al. [6] takes less than 35s to identify the road traffic operation safety risk. The method in this paper takes the shortest time to identify the road traffic operation safety risk and has the highest identification efficiency.

4. Conclusion

In view of the poor effect and low efficiency of traditional methods for road traffic operation safety risk identification, this paper proposes a road traffic operation safety risk identification method considering traffic conflict. By analyzing the mechanism of traffic conflict, under the principles of comprehensiveness, guidance and scientificity, the traffic conflict indicators are selected, and the data of the selected traffic conflict indicators are filled with gaps, outliers removed and de-noised. Based on the preprocessing results, the frequency of traffic conflict is predicted by constructing a random response negative binomial model, and the probability of occurrence of road traffic operation safety risk is calculated by using the maximum membership method, According to the calculation results, the risk level of road traffic operation safety is divided to realize the identification of traffic operation safety risk. According to the experiment, the road traffic operation safety risk identification method in this paper has the best effect and the highest identification efficiency. The innovation of this method lies in:

(1) The accuracy of road traffic operation safety risk identification based on this method can reach 98%, and the identification effect is good.

(2) The method in this paper takes less than 18s to identify the risk of road traffic operation safety. The identification time is shorter and the identification efficiency is higher.

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How to realize urban road traffic status recognition in the context of the internet of vehicles

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Abstract

The traffic flow model is a complex dynamic problem, which has the characteristics of high-dimensional, time-varying, nonlinear and so on. Therefore, the mathematical model established by the traditional theory cannot accurately describe the characteristics of the traffic flow, and cannot accurately identify the traffic state. This paper studies the recognition of urban road traffic status in the context of the Internet of Vehicles. First of all, the V2X data communication scheme is designed to realize the transmission and sharing of vehicle and road information through the use of V2X technology; Then, combining the probability density of traffic flow distribution and the characteristic distribution of traffic flow, the characteristics of road traffic state are extracted; Finally, based on the traffic state characteristics, a hidden Markov model of traffic state characteristics is established, and the traffic state identification is realized by finding the optimal state sequence to reflect the traffic state in the current time window. The experiment shows that compared with the traditional traffic state recognition method, this method has more accurate recognition accuracy and shorter recognition time.

Keywords - internet of vehicles, urban road, traffic status, data sampling, characteristic analysis, status identification

1. Introduction

The problem of traffic congestion on urban roads has become the focus of public attention. It has seriously affected people's daily life and work as well as the sustainable development of the city, causing huge economic losses to the society. Accurate and real-time identification of road traffic status and timely release of road traffic status information can provide reasonable travel plans for traffic participants, play a role in reasonable organization and effective dispersion of traffic flow, and reduce the impact of traffic congestion.

With the development and progress of information technology, big data, cloud computing and Internet of Things technology, the urban traffic management department has collected massive traffic data. However, due to the poor correlation between different traffic flow detection devices, the integration effect of these data is also poor [1]. How to find the information that can reflect the characteristics of urban traffic flow parameters from a large number of seemingly unrelated traffic flow data, and judge the road traffic status according to the changes of traffic flow parameter characteristics is a typical pattern recognition problem. On the one hand, this pattern recognition is faced with the dilemma of lacking prior knowledge due to the lack of complete data in the early stage, and on the other hand, due to many environments that affect the traffic status, including special weather, holidays, road grades, rush hours, etc., the traffic status is characterized by uncertainty, randomness and dynamics [2, 11]. Therefore, it is of great significance to design an effective urban road traffic status recognition method for real-time control of road traffic status and timely control of traffic flow.

For this reason, support vector machines are used to identify urban road traffic status in Li et al. [5]. In the recognition process, in order to optimize the generalization ability of support vector machine, genetic algorithm is introduced. Through global optimization, the optimal penalty coefficient and kernel function parameters are obtained, and the optimized support vector machine is used to identify the urban traffic state. Zhu et al. [19] combines the Davidsonburgen index with sparse track data to identify the traffic status. In this study, on the basis of processing vehicle track data and road network data, a road segment data set based on time series is constructed. Then, the best vehicle queue is established by using the Davidson Boding index, and then multiple vehicle queues are formed into traffic flow clusters. Finally, the traffic flow is classified by C-means clustering to identify the traffic status. Wang et al. [10] designed an urban traffic state recognition method based on optimizing Inception-ResNet-v2. In this study, aiming at the conventional Inception-ResNet-v2 algorithm, SENet attention mechanism is used to optimize the Inception-ResNet-C unit and improve its learning ability. On this basis, the road traffic features of different levels are fused and processed by feature fusion, and then the road traffic images of any scale are received in the full convolution structure, and the road traffic status is recognized by feature learning.

However, in practical applications, it is found that the traditional methods have poor performance in the precision of road traffic data and the retention rate of recognition results. To solve this problem, this study is based on the Internet of Vehicles environment, and studies the methods of urban road traffic status recognition. The specific research ideas are as follows:This method first obtains vehicle driving data through the introduction of intelligent on-board information unit, uses V2X technology to transmit and share vehicle-road information, and uses V2X technology to divide the acquired vehicular network data into four parts: vehicle operation data, on-board unit OBU data, roadside unit RSU data and background service data.Secondly, the road traffic grid is divided according to the collected data of the Internet of Vehicles, and the vehicle-mounted positioning system is used to sample the urban road traffic status information to clarify the relationship between the traffic flow and density. Thirdly, according to the traffic status information sampling results, the second step of the traffic flow in the road is established, and then combined with the probability density of the traffic flow distribution and the characteristic distribution of the traffic flow, the characteristics of the road traffic status are analyzed. According to the dynamics and continuity of urban road traffic state changes, around the average speed, contrast and inverse variance of vehicles within a fixed time window, four states are divided by cluster analysis: smooth, smooth, congested and blocked.Finally, the road traffic state evolution is simplified as a Markov process, and the road traffic state is hidden. A fixed time window is set to train the hidden Markov model, and the traffic state in the current time window is reflected by the optimal state sequence, so as to complete the identification of the urban road traffic state. The innovation of this method is that based on the spatial structure of the Internet of Vehicles environment, a V2X data communication scheme is designed. Through data interaction in the form of vehicle and vehicle, vehicle and base station, and base station and base station, data cross collision in the link is avoided, and the communication capability of the Internet of Vehicles is optimized.

2. Analysis and data acquisition of Internet of Vehicles environment

When accurately identifying its road traffic status, the first step is to improve the ability to obtain data from the Internet of Vehicles. This study is mainly based on the spatial structure environment of the Internet of Vehicles, and uses V2X technology in the Internet of Vehicles system to achieve the acquisition of urban road traffic information.

2.1. Analysis of Internet of Vehicles environment

Firstly, the spatial structure of the Internet of Vehicles environment is analyzed, and its structure is shown in Figure 1.

The Internet of Vehicles environment mainly realizes data interaction and sharing through multiplexing cellular networks, and uses the link between cellular network nodes and base stations, and the link between cellular network nodes and users to realize the transmission and reception of Internet of Vehicles data[4, 6]. In this process, the cellular network base station can implement unified processing of the data of the Internet of Vehicles, making the anti-interference ability of the data transmission process stronger. In the uplink transmission process, the data sending end in V2X structure will interfere with the fixed base station, causing the base station to receive interference data from the other terminals in the same local area network, resulting in confusion and even link multiplexing [13, 12]. Therefore, this study calculates the link SIR and analyzes the link multiplexing problem according to the calculation results.

If g_k represents the data transmission gain on link k of the Internet of Vehicles, and p_k represents the data transmission power on link k, the calculation process of the signal-to-noise ratio $\left(\frac{S}{N}\right)_k$ in link k is as follows:

$$\left(\frac{S}{N}\right)_k = \frac{R \times p_k}{g_k - G^2} \tag{1}$$

where G represents the Gaussian white noise in the link, and R represents the multiplexing relationship between binary variables. According to formula (1), for the link multiplexing problem with mutual interference, if the link power is increased to improve the signal to noise ratio of the link. Although it can reduce the data bit error rate, it will also cause interference to the rest of the links, thus aggravating the link multiplexing problem. At this time, other links will also use the same way to improve the signal-to-interference ratio by increasing the link power, which will add interference to the original multiplex link and create a vicious circle [15, 3]. In order to avoid the above problems as much as possible, this study optimized and designed V2X data communication scheme of the Internet of Vehicles, as shown in Figure 2.

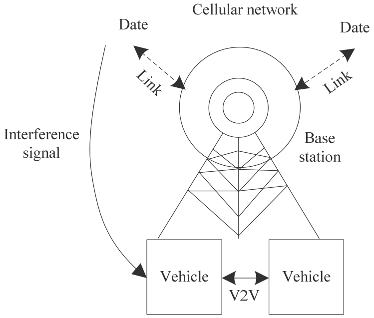

Fig. 1- Spatial structure diagram of the Internet of Vehicles environment

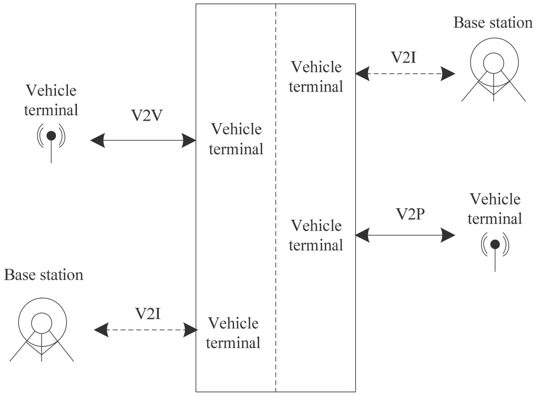

Fig. 2 - V2X data communication scheme

V2X data communication scheme in Figure 2 can ensure that the base station can receive the vehicle terminal data and traffic environment data in real time. Through targeted data interaction between vehicles, vehicles and base stations, and base stations and base stations, data cross collision in the link can be effectively avoided, thus effectively reducing the impact of multiplexing interference, and optimizing the communication capacity of urban road traffic.

2.2. Real-time acquisition of Internet of Vehicles data

After completing the analysis of the space environment of the Internet of Vehicles and optimizing the design of the data communication scheme of the Internet of Vehicles, it is necessary to use the existing communication scheme to obtain effective real-time data of the Internet of Vehicles. In order to ensure the reliability of data collection, this study introduces an intelligent on-board information unit to obtain vehicle driving data, and uses V2X technology to transmit and share vehicle route information. The real-time acquisition process of the Internet of Vehicles data is shown in Figure 3.

The vehicle networking data obtained through V2X technology is divided into four basic structures, which are the operation data of networked vehicles, on-board unit OBU data, roadside unit RSU data and background service data. Including:

① The operation data of the networked vehicle is mainly obtained from the real-time data in the on-board terminal, which can be directly exported by introducing CAN bus;

② On-board unit OBU data can obtain intersection information data from both sides of urban traffic roads through wireless communication transmission;

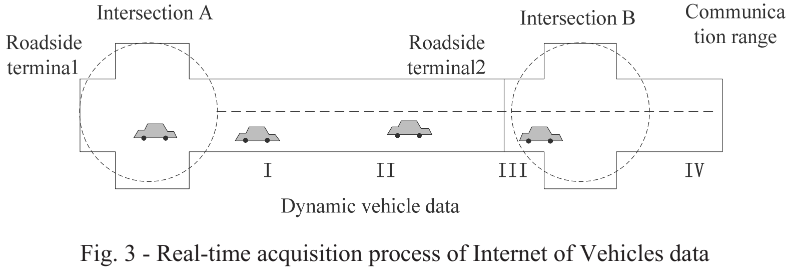

Fig. 3 - Real-time acquisition process of Internet of Vehicles data

③ The roadside unit RSU data can realize the preliminary evaluation of the road section operation status by integrating the local traffic road intersection information and vehicle data information;

④ Background service data is all data collected from the above three units to identify urban road traffic status.

From the real-time data acquisition process shown in Figure 3, it can be seen that when a vehicle leaves its location to reach Point I, it can record its driving data through V2X technology. When it leaves the next intersection to reach Point IV, it can upload all the acquired data to RSU2. When a vehicle moves into the communication area (point II), more stable V2X communication mode can be established at both ends of the communication. When the vehicle continues to drive to the second intersection and reaches point III, since OBU data acquisition has been completed at the first intersection, the acquisition of RSU2 data can be directly obtained through the transmission channel of RSU1, that is, by acquiring the data of each vehicle on the urban traffic road, to achieve real-time acquisition of all the data required for its identification. At the same time, based on the application advantages of V2X technology, it can provide data processing and analysis functions for subsequent data fusion, thus ensuring the stability of data in the subsequent evaluation process and providing more favorable conditions for evaluation.

3. Identify urban road traffic status

After the collection of urban road vehicle data, the design of urban road traffic status recognition method is completed. First of all, the urban road traffic status information is sampled from a large number of vehicle network data, and the road traffic status characteristics are analyzed according to the sampling results, and then the recognition is completed.

3.1. Sampling of urban road traffic status information

In order to effectively collect urban road traffic information, the road traffic grid model is divided in the form of cloud grid integrated scheduling. In the vehicle network environment, the on-board positioning system is used to extract the required data, as shown in Figure 4.

Considering the multi-input characteristics of urban road traffic, the fuzzy statistics of road traffic flow are carried out to obtain:

$$f(t) = \{f_1(t), f_2(t), \cdots, f_\sigma(t)\} \tag{2}$$

where $f(t)$ represents the fuzzy statistical result of road traffic flow, σ represents the decision vector of traffic flow distribution, and t represents time [8]. On this basis, in view of the complexity and volatility of urban roads, the partition matrix is established in the road traffic grid model as follows:

$$J(\sigma) = \begin{Bmatrix} \frac{\partial \tau f_1(t)}{\partial t_1} & \frac{\partial \tau f_1(t)}{\partial t_2} & \cdots & \frac{\partial \tau f_1(t)}{\partial t_n} \\ \frac{\partial \tau f_2(t)}{\partial t_1} & \frac{\partial \tau f_2(t)}{\partial t_2} & \cdots & \frac{\partial \tau f_2(t)}{\partial t_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial \tau f_\sigma(t)}{\partial t_1} & \frac{\partial \tau f_\sigma(t)}{\partial t_2} & \cdots & \frac{\partial \tau f_\sigma(t)}{\partial t_n} \end{Bmatrix} \tag{3}$$

where τ represents the dynamic load of road traffic flow. After the partition matrix is established, the traffic status information of each matrix is extracted and sampled, and the final sampling result is obtained by summarizing.

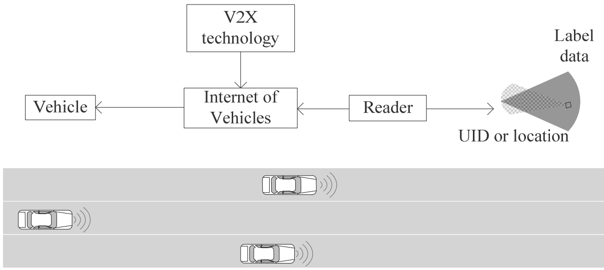

Fig. 4 - Sampling process of urban road traffic data

In a single partition matrix, the traffic parameter ε is set to describe the changes of road traffic in different times. At different times, the degree of deviation from the steady state of the road traffic state can be measured by the steady state evaluation index. The operating state of the divided traffic sections is as follows:

a. Steady state set S_1:

$$S_1 = \{\varepsilon | \sup(S) - \varepsilon \geq \vartheta || \varepsilon - \inf(S) \geq \vartheta |\} \tag{4}$$

where $\sup(S)$ and $\inf(S)$ represent the upper and lower supremum of the interval of the steady-state set, respectively, and ϑ represents the steady-state decision threshold.

b. Unstable set S_2:

$$S_2 = \{\varepsilon | \sup(S) - \varepsilon < \vartheta || \varepsilon - \inf(S) < \vartheta |\} \tag{5}$$

On this basis, the second-rate theory is introduced to describe the state level and congestion state of road traffic. The vehicles on the road are divided into two types: stopped vehicles and moving vehicles. $\bar{v}$ represents the average speed of running vehicles on the road, and its expression is as follows:

$$\bar{v} = v_{max} \times (1 - g_s)^{\gamma+1} \tag{6}$$

where v_{max} represents the maximum speed of the vehicle in the road network, g_s represents the parking proportion, and γ represents the damping parameter of the traffic network.

According to the observation data of the road network and based on the second-rate theory, the parking proportion coefficient of the road network is fitted, and the process is as follows:

$$g_s{}' = g_{s-min} + \left(\frac{\rho}{\rho_j}\right)^{\delta} (1 - g_{s-min}) \tag{7}$$

where g_{s-min} represents the minimum value of parking proportion, ρ represents the average traffic flow density, ρ_j represents the congestion density, and parameter δ is mainly used to measure the service quality of the road network [16, 18].

Based on the above formula, the flow-density model of urban road traffic is established as follows:

$$W = \rho v_{max} (1 - g_{s-min})^{\gamma+1} \left(1 - \left(\frac{\rho}{\rho_j}\right)^{\delta}\right)^{\gamma+1} \tag{8}$$

where W represents the average traffic flow on the road [14]. The result obtained in formula (8) is the sampling result of urban road traffic status information.

3.2. Analysis of road traffic state characteristics

Complete the sampling of urban road traffic status information from the Internet of Vehicles data through the above process, and on this basis, analyze the characteristics of road traffic status.