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Contents

Y. Luo	3	Evaluate of the impact of concrete bridge construction on vehicle traffic capacity
D.J. Zhang, F.M. Shang	15	Association recognition method for bad driving behavior on urban road sections: multi class Adaboost algorithm
Y. Yao, A.J. Wang, F.M. Shang	29	Dynamic obstacle avoidance path planning method for autonomous driving based on quantum ant colony algorithm
J.W. Fang, P. Huang	41	Comprehensive governance of traffic safety based on composite factors of socio economic environment
J.Y. Li	53	Analysis of factors influencing urban road traffic accidents using weighted association rules
Y. Zhang, C.Y. Zhang, H. Feng, C.X. Huang, Y.F. Tong	67	Short term traffic flow prediction of urban road network driven by spatiotemporal data
M. Yi, C.Y. Yan	77	Optimization method for logistics distribution path of unmanned vehicles under vehicle road collaboration
S.F. Deng, Y. Yang, Z.W. Jie	89	Spatial pattern and coupling coordination level of regional transportation and economic development
F. Guo, Y.T. Zhou, S. Qiu, H.L. Jiao, X. Zhang	103	Automatic parking path tracking control considering the influence of atmospheric conditions
H. Feng, C.X. Huang, S. Qiu, C.Y. Zhang, Y.T. Zhou	113	Traffic accident prediction method based on improved support vector machine

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X.G. Zhang, L. Liao	129	Identification methods for driver's dangerous driving behavior in low visibility environments
B. Cai	143	Urban rail transit path connection planning method based on federated learning and computer immune algorithm
X. Zhang, H.L. Jiao, Y. Zhang, Z.K. Li, C.Y. Zhang	157	Fatigue driving recognition of truck drivers based on multi-feature fusion
S. Qiu, H.L. Jiao, F. Guo, Y.T. Zhou, C.X. Huang	169	Loss prediction of urban road traffic accidents under variable weight TOPSIS method and modified entropy weight
Y.F. Tong, Z.K. Li, Y. Zhang, H. Feng, H.L. Jiao	179	The application of deep dual q network in urban rail transit network planning
T. Liu, H.D. Su	191	Intelligent prediction method of urban road traffic congestion based on knowledge graph technology

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Evaluate of the impact of concrete bridge construction on vehicle traffic capacity

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Abstract

During the construction of concrete bridges, vehicle traffic capacity frequently experiences significant disruptions. To assess this impact, this article conducts a new comprehensive evaluation method. Initially, we calculate the equivalent speed and density of traffic on the construction section, subsequently analyze the functional relationship between these two parameters. By categorizing traffic into three distinct flow states, we compute the traffic congestion index. Furthermore, we establish a multi-lane traffic capacity model to estimate the vehicle traffic capacity during concrete bridge construction. This estimated capacity is then compared with pre-construction traffic capacity data. Experimental results reveal that the traffic capacity reduction rate and traffic flow change rate calculated using new methodology align well with actual values, thereby validating the high accuracy of new evaluation approach in assessing the impact of construction on vehicle traffic capacity.

Keywords - concrete bridge construction, vehicle capacity, equivalent vehicle speed, equivalent density

1. Introduction

In urban transportation construction, concrete bridges are an important component of urban transportation, and their construction and improvement can improve the level of urban transportation, promote the development and prosperity of urban economy [10]. The construction of concrete bridges is a crucial link in ensuring the quality and safety of bridges, and has a significant impact on the smoothness and efficiency of traffic. As a key node in the transportation network, its construction process inevitably affects the traffic capacity of vehicles. The occupation and closure of the road surface during the construction of concrete bridges will directly lead to a reduction in the number of lanes, thereby affecting the traffic capacity of vehicles [4]. For example, temporary fences and parking of construction vehicles may be required in the construction area, which will occupy the road space originally used for vehicle traffic. The original multi lane road may become a single lane or narrower passage, leading to a decrease in vehicle speed and being affected by factors such as traffic control during construction and the installation of temporary traffic signals. These measures will also affect the vehicle's traffic capacity to a certain extent [1]. Among them, restricting the passage of large vehicles may increase the load pressure on other vehicles, while the setting of temporary traffic lights may lead to traffic congestion and delay [9]. The quantitative evaluation of vehicle traffic capacity during the construction of concrete bridges can provide accurate traffic flow prediction and control plans for traffic management departments, thereby promoting the smooth operation of urban economy and helping to optimize traffic planning and design. Through in-depth analysis of traffic bottlenecks and potential risks during the construction process of concrete bridges, more scientific and reasonable suggestions can be provided for future bridge design and construction.

Yi et al. [17] uses the cellular transmission model to calculate and evaluate the traffic capacity of toll station intersections on highways. The research area was divided into regular shaped cellular cells, and a station front traffic capacity model was constructed based on cellular transmission mechanism to determine the degree of congestion in the area. The theoretical traffic capacity of the area was calculated considering different lanes and configurations. However, this method ignores the linear relationship between driving speed and vehicle density, which may lead to a decrease in the accuracy of traffic capacity calculation and evaluation. Wang et al. [13] proposes using a multi-layer fuzzy algorithm to calculate the traffic capacity of road network areas. Based on fuzzy logic rules, a macro analysis is conducted to study the correlation between factors affecting the traffic capacity of regional road sections. A fuzzy judgment subsystem for traffic capacity is constructed, and the factors affecting traffic capacity are treated as multiple characteristic values to calculate the traffic capacity of the regional road section under dynamic conditions. However, there are many factors that affect road traffic, and this method does not pay attention to the difference between free flow and congested flow, which affects the effectiveness of traffic capacity evaluation. Yue et al. [18] conducted a study on the traffic situation of bidirectional parking control intersections, considering the impact of pedestrian crossings on the traffic capacity of secondary roads. An analytic hierarchy process model was constructed, and the traffic flow at intersections was statistically analyzed using on-site collected data. Sensitivity analysis of factors affecting road traffic capacity was conducted using random simulation methods to evaluate the impact of pedestrian crossings on the traffic capacity of bidirectional parking control intersections. However, the Analytic Hierarchy Process (AHP) model cannot consider the issue of multiple lanes, and only conducts sensitivity analysis from the perspective of influencing factors, which may result in significant errors between the evaluation results and actual results.

Therefore, this article conducts an evaluation study on the impact of concrete bridge construction on vehicle traffic capacity.

2. Design of evaluation method for the impact of concrete bridge construction on vehicle traffic capacity

2.1. Regression analysis of the functional relationship between equivalent vehicle speed and equivalent density

During the construction of concrete bridges, vehicle traffic capacity is often severely affected. To ensure smooth and safe road traffic during the construction of concrete bridges, it is necessary to scientifically evaluate the impact of concrete bridge construction on vehicle traffic capacity. During this process, calculating the equivalent vehicle speed and equivalent density is of great significance [15]. Equivalent vehicle speed is an indicator that reflects the speed changes of vehicles in the construction area of concrete bridges. Due to the possible narrowing of roads, reduction of lanes, and speed limits in the construction area of concrete bridges, the driving speed of vehicles will be greatly affected [6]. Calculating the equivalent vehicle speed can help understand the overall situation of vehicle speed during concrete bridge construction, and thus evaluate the impact of concrete bridge construction on vehicle traffic capacity. And equivalent density is an indicator reflecting the density of vehicles in the construction area of concrete bridges. During the construction of concrete bridges, due to limited road traffic capacity, vehicles may queue up in front of the concrete bridge construction area, leading to an increase in vehicle density [7]. Calculating the equivalent density can further understand the distribution of vehicles in the construction area of concrete bridges, thereby determining the specific impact of concrete bridge construction on road traffic capacity. Therefore, by comprehensively considering equivalent vehicle speed and equivalent density, the impact of concrete bridge construction on vehicle traffic capacity can be more comprehensively evaluated.

The ratio of road length to required travel time in the construction section of concrete bridges is defined as the equivalent vehicle speed $\bar{v}$, which can reflect the actual driving efficiency of vehicles in the construction area of concrete bridges. At the same time, in order to measure the level of traffic congestion on the roads in the construction area of concrete bridges, the average traffic volume of each section on the actual road is defined as the equivalent traffic volume of the road, that is, the equivalent flow $\bar{q}$. This flow indicator can reflect the overall flow of vehicles on the road during the construction of concrete bridges. In order to more accurately evaluate the impact of concrete bridge construction on vehicle traffic capacity, a relationship model between flow density and speed can be used to further calculate the maximum traffic volume of the equivalent road in an ideal state [8]. This maximum traffic volume is the equivalent capacity of urban roads, representing the potential limit of the road's ability to accommodate and handle vehicle traffic during the construction of concrete bridges.

Therefore, during the construction of concrete bridges, the calculation formula for the equivalent speed and equivalent density of traffic on the construction section of concrete bridges can be expressed as follows:

$$\begin{cases} \bar{v} = \frac{L}{T} \\ \bar{k} = \frac{\bar{q}}{v} \end{cases} \tag{1}$$

where L represents the length of the road section for concrete bridge construction; T represents the travel time required for the construction of concrete bridge sections.

When the road traffic density is low and congested during the construction of concrete bridges, the relationship model between the traffic speed v and the flow density k on the construction section of concrete bridges can be expressed as follows:

$$v = \begin{cases} v_f \ln = \bar{v}\frac{-\bar{k}}{k_m}, k \in [0, k_m] \\ v_m \ln = \bar{v}\frac{k_j}{\bar{k}}, k \in \left[k_m, k_j\right] \end{cases} \tag{2}$$

$$k_m = \frac{k_j}{\mathrm{e}}; v_m = \frac{v_f}{\mathrm{e}} \tag{3}$$

where v_f represents the free flow speed of road traffic during the construction of concrete bridges; v_m represents the corresponding traffic speed during the construction of concrete bridges under the most congested conditions of road traffic density (congested flow); k_m and k_j respectively represent different road blockage densities during the construction of concrete bridges, k_m is the blocking density at free flow velocity, k_j is the congestion density at the peak of traffic density (congested flow); e represents the road resistance index.

The traffic volume Q can be represented by $Q = kv$. By calculating the equivalent speed and density of concrete bridge construction sections, Origin software can be used to perform regression analysis on the functional relationship between the equivalent speed $\bar{v}$ and the equivalent density $\bar{k}$. The regression analysis results in a comparison between the speed and density function equation and equation (2), and then calculate the congestion density of the exit section [2]. The relationship between velocity and density obtained from some regression analyses is shown in Table 1.

The logarithmic and exponential fitting curves of the relationship between speed and density are shown in Figures 1 and 2.

Tab. 1 - Regression analysis of the relationship between velocity and density function

Function	Functional relationship	R^2
Logarithmic type	y=45.48913-7.53505ln$x$	0.95823
Exponential type	y=20.43524e$^{-0.00687x}$	0.96376

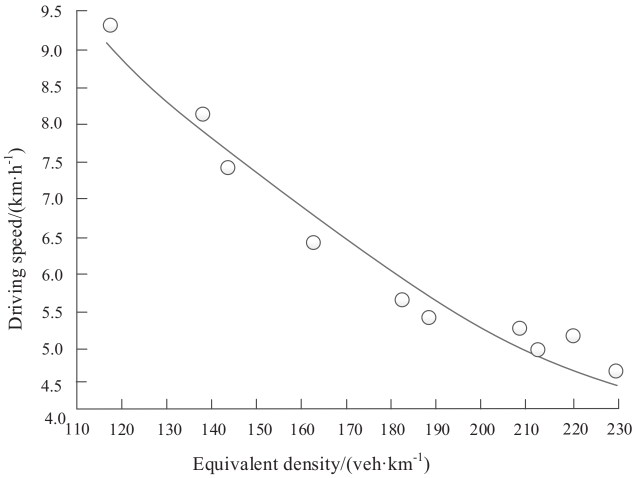

Fig. 1 - Logarithmic fitting curve of velocity density relationship

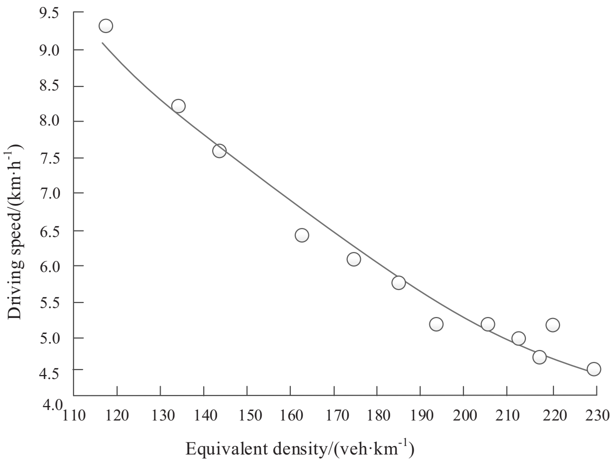

Fig. 2 - Exponential fitting curve of velocity density relationship

2.2. Calculation of free travel time on road segments based on road resistance function

The BPR function (Bureau of Public Roads Function) is developed for continuous flow transportation facilities and is mainly used to describe the relationship between traffic flow, speed, and density [5]. However, when the research object shifts to the construction area of urban concrete bridges, the traffic conditions will undergo significant changes. The construction area is often accompanied by special situations such as road narrowing, reduced lanes, speed limits, and traffic control, all of which can affect the normal relationship between traffic flow, speed, and density [3]. Therefore, when applying the BPR function to the impact evaluation of vehicle traffic capacity in urban concrete bridge construction areas, it is necessary to modify the function. The purpose of the revision is to more accurately reflect the special traffic conditions in the construction area, in order to obtain more realistic vehicle traffic capacity evaluation results [16]. Establish a model with BPR function, which calculates the free travel time through the construction section of a concrete bridge. The calculation formula can be expressed as:

$$T(t) = t_0\left\{1 + \alpha\left[\frac{q_1 - q(t)}{c_1 - c(t)}\right]^{\beta}\right\} \times Q \tag{4}$$

where $T(t)$ represents the free travel time through the concrete bridge construction section at time t; t_0 represents the free travel time of the concrete bridge construction section; q_1 represents the traffic flow of the road section before construction; $q(t)$ represents the traffic flow during the construction of concrete bridge sections; c_1 represents the equivalent traffic capacity of the road section before construction; $c(t)$ represents the equivalent traffic capacity of the concrete bridge construction section at time t; α and β represent the correction parameters for different traffic flow states, respectively.

Concrete bridges are usually designed with 3 to 4 lanes in both directions, mainly carrying four wheeled motor vehicles. Although two - and three wheeled vehicles account for a relatively small proportion on such bridges, they cannot be ignored in traffic flow, and their impact on traffic capacity needs to be reflected through the correction coefficient of along the way conditions [12]. When evaluating traffic capacity, small cars are set as standard vehicles in order to convert the traffic volume of other types of vehicles into the equivalent traffic volume of small cars according to corresponding conversion factors. In order to better adapt the BPR function to the special traffic conditions in the construction area of concrete bridges, it is necessary to adjust the correction parameters α and β in the BPR function. This involves calibrating the model parameters to reflect the actual situation under different traffic flow operating states. After such modifications, suitable BPR correction models for different traffic flow operating states can be obtained, and the BPR model can be logarithmically processed. The specific calculation formula is as follows:

$$\ln\left[\frac{T(t)}{t_0} - 1\right] = \ln\alpha + \ln\beta\left[\frac{q(t)}{c(t)}\right] \tag{5}$$

After completing the logarithmic processing of the BPR model, based on the internal operating conditions of traffic flow and their feelings towards drivers and passengers, traffic flow can be divided into three states: free flow, blocked flow, and congested flow. This helps to more accurately describe and understand the characteristics of traffic flow in different situations, and thus more effectively evaluate vehicle capacity [19]. Using the Traffic Congestion Index (TSI) to divide three traffic flow states: free flow, blocked flow, and congested flow, the TSI calculation formula is as follows:

$$\mathrm{TSI} = 100\left(1 - \frac{T_0}{T_1}\right) \tag{6}$$

where T_0 represents the free flow passage time of the selected road section for the construction of concrete bridges; T_1 represents the actual travel time selected. The three congestion status intervals are divided, as shown in Table 2.

According to the traffic flow state intervals obtained from Table 2, regression calculations were conducted using SPSS software to analyze the values of the correction parameters α and β in the BPR correction model, as shown in Table 3.

Tab. 2 - Traffic flow status interval table

Traffic flow status	Free flow	Blocking flow	Congestion flow
Traffic congestion index TSI interval value	0<TSI<25	25≤TSI<70	70≤TSI≤100

Tab. 3 - BPR correction model correction parameter values table

Traffic flow status	α	β
Free flow	0.4825	2.7533
Blocking flow	1.1156	2.9105
Congestion flow	2.1065	0.6510

According to three congestion state intervals, the determined correction parameters α and β are inputted into formula (4), and the BPR correction model is used to obtain the free travel time of the concrete bridge construction section. The calculation formula is as follows:

$$T(t)=\begin{cases} t_0\left\{1+0.4825\left[\frac{q(t)}{c(t)}\right]^{2.7533}\right\}\times Q, \text{Free flow} \\ t_0\left\{1+1.1156\left[\frac{q(t)}{c(t)}\right]^{2.9105}\right\}\times Q, \text{Blocking flow} \\ t_0\left\{1+2.1065\left[\frac{q(t)}{c(t)}\right]^{0.6510}\right\}\times Q, \text{Congestion flow} \end{cases} \tag{7}$$

2.3. Impact evaluation based on a multi lane capacity model

During the construction of concrete bridges, evaluating the impact on vehicle traffic capacity is a crucial step in ensuring road safety and smoothness. Building capacity models with different numbers of lanes (such as 3 lanes and 4 lanes) is of great significance. The traffic capacity of bridges or sections with different numbers of lanes varies under the same construction conditions. The multi lane capacity model is a mathematical model used to predict and evaluate the maximum traffic flow that a lane road or section can carry under specific conditions, which can estimate the maximum number of vehicles passing through the section in a given time [11]. By constructing a model with a specific number of lanes, the impact of concrete bridge construction on traffic flow can be more accurately evaluated, thereby formulating more reasonable traffic management strategies. During the construction of concrete bridges, it is possible that the original 3-lane or 4-lane sections may have fewer lanes due to factors such as road occupation. Therefore, taking the 3-lane and 4-lane sections as an example, the traffic capacity of vehicles in the construction of concrete bridges can be expressed using the following formula:

$$C=\begin{cases} c_3=c_{3g}+c_{3t}\times h_{d(3-i)} \\ c_4=c_{4g}+c_{4t}\times h_{d(4-i)} \end{cases} \tag{8}$$

where $\mathrm{c_{3g}}$ and $\mathrm{c_{4g}}$ represent the vehicle traffic capacity for construction sections with 3 lanes and 4 lanes, respectively; $\mathrm{c_{3t}}$ and $\mathrm{c_{4t}}$ respectively represent the vehicle traffic capacity in the presence of construction occupation when the construction section is 3 lanes and 4 lanes; d represents the average headway; i represents the number of occupied lanes.

Regardless of whether the construction occupies the outer lane z_1 or the inner lane z_0, the lane edge traffic capacity characterization weight $w=w_1,w_0$ is assigned, which measures the difficulty of changing lanes and will have a certain impact on vehicle traffic. Although the driving characteristics of changing lanes are the same under the conditions of 3-lane and 4-lane road sections, the travel time and traffic flow are different [20]. Therefore, combining multiple variable factors, a multi lane traffic capacity model is constructed to calculate the vehicle traffic capacity under concrete bridge construction. The calculation formula is as follows:

$$\Delta C=\begin{cases}\Delta c_3=\dfrac{r(c_{3g}+c_{3t})(S_1,S_0)}{z_{t1}[1-h_{d(3-i)}]z_{t0}[1-h_{d(3-i)}]}\times wh_{d(3-i)}\\ \Delta c_4=\dfrac{r(c_{4g}+c_{4t})(S_1,S_0)}{z_{t1}[1-h_{d(4-i)}]z_{t0}[1-h_{d(4-i)}]}\times wh_{d(4-i)}\end{cases} \tag{9}$$

where r represents the characterization of lane side traffic capacity; z_{t1} and z_{t0} respectively represent the passage time of vehicles under construction conditions where the outer lane z_1 and inner lane z_0 are occupied; S_1 and S_0 respectively represent the maximum traffic flow of the construction section under the occupied construction conditions of the outer road z_1 and the inner road z_0.

Compare the vehicle capacity calculated by the multi lane capacity model with the pre construction capacity data. If the traffic capacity during construction is significantly lower than before, it indicates that construction has had a negative impact on vehicle traffic capacity [14].

At this point, the impact evaluation of vehicle traffic capacity under concrete bridge construction has been completed. The specific process is shown in Figure 3.

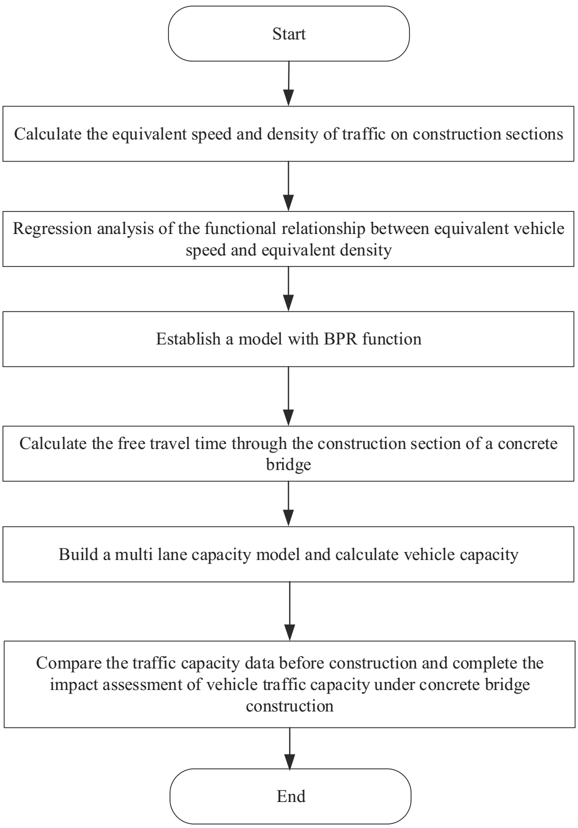

Fig. 3 - Impact evaluation process for vehicle traffic capacity under concrete bridge construction

3. Experiment

3.1. Experimental subjects

To verify the effectiveness of the method proposed in this article in evaluating the impact on vehicle traffic capacity, an experimental verification was conducted using an important concrete bridge reinforcement construction project in a certain city as an example. When the bridge was built, it was a prefabricated reinforced concrete T-shaped simply supported beam bridge with 27 spans and 26 piers, with a total length of 604.24 meters. It is a key node bridge on the urban main road, connecting the city center with important commercial and residential areas in the surrounding area. On the south side of the bridge, there is a large commercial complex connected, including shopping centers, catering and entertainment facilities, with a high daily traffic volume. The north side of the bridge is close to the residential area, with a dense population and a significant increase in traffic volume during peak commuting hours. The bridge has been in operation for 25 years, and there have been local concrete cracks on the bridge deck and sides. Therefore, reinforcement construction has been carried out on the concrete bridge. In order to reduce the impact on traffic, construction is scheduled during non peak hours, from 10:00 to 22:00 daily, for a total duration of three months. Due to construction needs, it is planned to occupy the outermost two lanes in the south to north direction of the bridge beam for reinforcement work. The remaining 6 lanes will remain open for vehicle traffic.

Possible detours may result in a slight decrease in traffic flow on roads near the construction area, but the overall traffic flow on the bridge remains at a relatively high level. During the mid-term of construction (the second month), as citizens gradually understand and adapt to construction information, the phenomenon of vehicle detours decreases, and the traffic flow of bridges gradually returns to pre construction levels. In the later stage of construction (the third month), as the construction approaches its end, the public's attention to the construction decreases, and the traffic flow of the bridge remains stable.

Collect vehicle traffic data within three months of construction, and use MATLAB simulation software to assist in evaluating changes in vehicle traffic capacity. The vehicle capacity evaluation method based on cellular transmission model proposed in reference [17] and the vehicle capacity evaluation method based on multi-layer fuzzy algorithm proposed in reference [13] will be used as comparative methods for this experiment, and will be compared with the method proposed in this paper to verify its feasibility.

Divide the bridge into 6 construction sections and calculate the changes in vehicle traffic capacity of each section during the mid-term of construction. The equivalent traffic capacity of each section is shown in Table 4.

Tab. 4 - Equivalent traffic capacity of each road section

Direction of passage	Equivalent traffic capacity of road sections ($pcu{\cdot}h^{-1}$)					
	Road section 1	Road section 2	Road section 3	Road section 4	Road section 6	Road section 6
Southbound	1378	805	1678	890	352	767
Northbound	1654	765	2005	758	423	876

3.2. Experimental indicators

Based on the experimental plan set above, select experimental validation indicators, and analyze the reduction rate of traffic capacity and the change rate of traffic flow as validation indicators in the experiment.

① Traffic capacity reduction rate: This indicator reflects the direct impact of construction on bridge traffic capacity. The reduction rate of traffic capacity before and after construction is statistically analyzed. The closer the results obtained by this method are to the actual results, the more accurate the evaluation method is in evaluating the impact of construction on traffic capacity. The formula for calculating the reduction rate of traffic capacity is as follows:

$$\widetilde{\Delta \mathrm{C}} = \frac{\Delta C}{c_1} \times 100\% \tag{10}$$

where ΔC represents the vehicle traffic capacity during the construction period; c_1 represents the equivalent traffic capacity of the section before construction.

② Traffic flow change rate: This indicator can display the impact of construction on bridge traffic flow. The closer the results obtained by this method are to the actual results, the more accurate the evaluation method is in evaluating the impact of construction on traffic capacity. The formula for calculating the rate of change in traffic flow is as follows:

$$\delta = \frac{q(t) - q_1}{q_1} \times 100\% \tag{11}$$

where $q(t)$ represents the traffic flow of this section during the construction period; q_1 represents the traffic flow of the section before construction.

3.3. Experimental results and analysis

3.3.1. Capacity reduction rate

In order to verify the accuracy of the method proposed in this article in evaluating the impact of vehicle traffic capacity, the method of this paper, Yi et al. [17] and Wang et al. [13] have been compared. Formula (10) was used to calculate the rate of traffic capacity reduction, and the calculation results of different methods on the rate of traffic capacity reduction during the construction period were compared with the actual rate of traffic capacity reduction. The method that is closer to the actual rate of traffic capacity reduction was used, resulting in higher evaluation accuracy. The comparison results are shown in Figure 4.

According to Figure 4, it can be seen that during the construction of concrete bridges, the reduction rate of traffic capacity for each section from 1 to 6 is not the same. Among them, the reduction rate of traffic capacity calculated by the two comparison methods varies greatly compared to the actual value, with significant errors; The reduction rate of traffic capacity calculated by the method in this article is consistent with the actual value, indicating that the accuracy of evaluating the impact of vehicle traffic capacity during construction is relatively high.

3.3.2. Traffic flow change rate

In order to verify the accuracy of the method proposed in this article for evaluating the impact of vehicle traffic capacity, the method of this paper, Yi et al. [17] and Wang et al. [13] have been compared to evaluate the impact of vehicle traffic capacity during the construction of the bridge. The traffic flow change rate was calculated using formula (11), and the calculation results of different methods on the traffic flow change rate during the construction period were compared with the actual traffic flow change rate. The method that is closer to the actual traffic flow change rate is more accurate in the evaluation. The comparison results are shown in Figure 5.

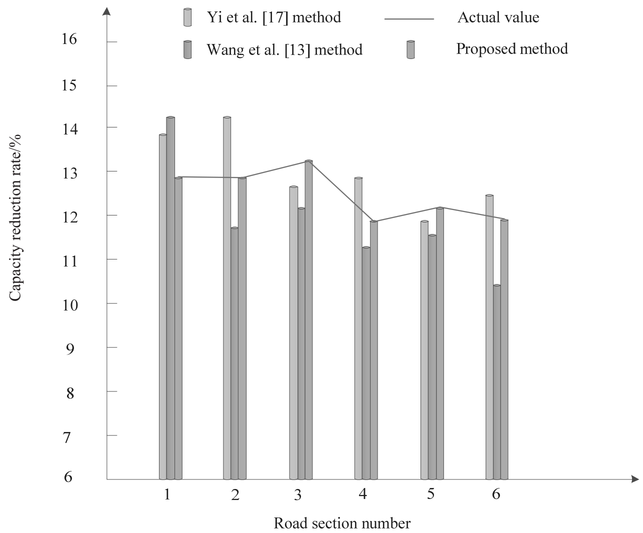

Fig. 4 - Comparison of capacity reduction rates by different methods

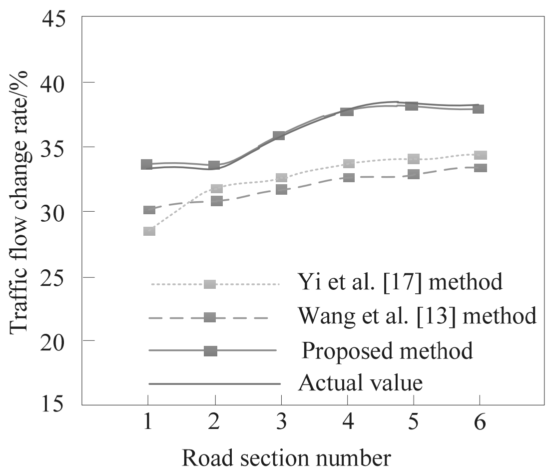

Fig. 5 - Comparison of traffic flow change rates using different methods

According to Figure 5, it can be seen that during the construction of concrete bridges, the traffic flow change rate of each section from 1 to 6 is not the same. Among them, the traffic flow change rates calculated by the two comparison methods are both lower than the actual traffic flow change rates, with significant errors; The traffic flow change rate calculated by the method in this article is in good agreement with the actual traffic flow change rate, indicating that the accuracy of evaluating the impact of vehicle traffic capacity during construction in this article is relatively high.

4. Conclusion

During the construction of concrete bridges, ensuring smooth vehicle traffic capacity is crucial for maintaining the efficient operation of urban transportation networks. This article provides an in-depth evaluation of the impact of concrete bridge construction on vehicle traffic capacity.

(1) By calculating the equivalent speed and density of the construction section, a model with BPR function is established, and the traffic congestion index under different state flows is considered to obtain the free travel time through the construction section; A multi lane traffic capacity model was used to accurately calculate the vehicle traffic capacity during construction, and compared with pre construction data to comprehensively evaluate the impact of construction on vehicle traffic capacity.

(2) The experimental results show that the method proposed in this article can accurately calculate the rate of capacity reduction and the rate of traffic flow change, which is consistent with the actual situation. This proves that the evaluation method used in this article has high accuracy and effectiveness, providing strong data support for traffic management during construction.

In future work, we will continue to improve this evaluation method, further consider more influencing factors, and improve the accuracy and applicability of the evaluation. At the same time, we will actively explore more effective traffic management measures to minimize the impact of construction on vehicle traffic capacity and ensure the smooth flow of urban transportation networks.

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Association recognition method for bad driving behavior on urban road sections: multi class Adaboost algorithm

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Abstract

Accurately and quickly identifying harmful driving behaviors is of great research significance. This article introduces a multi class Adaboost algorithm for accurately and quickly identifying harmful driving behaviors on urban roads. This method first carefully collects data related to bad driving behavior on road sections. Then, the optical flow method is used to capture images of driving behavior, and the TV-L1 optical flow method is used to refine the images to improve clarity. Finally, the CART decision tree serves as the cornerstone for constructing a rigorously trained weak classifier, strategically combining multiple individual weak classifiers to form a robust strong classifier. This powerful classifier is supported by the Adaboost algorithm and can provide detailed classification of bad driving behavior. To ensure a holistic assessment, fuzzy mathematics is deployed to discern behavioral risks, thereby facilitating the correlated identification of adverse driving patterns. Experiment results verifies the efficacy of our approach, with recognition time dwindling to a mere 1.9 seconds and the accuracy of correlated recognition soaring to an impressive 99.8%.

Keywords – multi class Adaboost algorithm, bad driving behavior, association recognition, urban RD, cart decision tree

1. Introduction

The identification technology of bad driving behavior can help traffic law enforcement departments more effectively enforce traffic regulations, supervise and punish illegal driving behavior, enhance the deterrent power of the law, promote drivers to comply with traffic rules, and provide a basis for driving training and safety education [4, 12, 6]. The identification data of bad driving behavior can provide reference for urban traffic planning and management, helping decision-makers understand traffic conditions. In summary, the research on identifying bad driving behavior on urban road sections not only helps to improve traffic safety, but also promotes the development of intelligent transportation systems [8, 16], strengthens regulatory enforcement and supervision, promotes the improvement of driving behavior, and provides support for urban management, which has important social and economic value.

Luo et al. [7] proposed a study on identifying bad driving behavior on urban road sections based on channel attention YOLOV5s. YOLOV5s was chosen as the basic model, and channel attention mechanism was introduced to enhance the sensitivity of the model to key features. The YOLOV5s model was used to extract bad driving behavior, allowing the model to adjust the weights of different features and better capture features related to bad driving behavior. Optimize model performance through methods such as hyperparameter adjustment. Deploy the trained model into an actual traffic monitoring system to identify and analyze bad driving behavior in real-time. However, due to increased complexity, the time required for data processing will increase. Shen et al. [9] proposed a dual channel model based on the human visual cortex for identifying bad driving behavior on urban road sections, and constructed a dual channel model of the human visual cortex. The model should include two subsystems, corresponding to the functions of ventral flow and dorsal flow, respectively. The ventral flow subsystem is used to identify traffic participants such as vehicles and pedestrians, while the dorsal flow subsystem is used to detect the movement status and position of vehicles. Extract features from video or image data, including abnormal vehicle movement and driver distraction behavior, train the model using annotated dataset of bad driving behavior, and adjust model parameters to optimize recognition performance. However, the existing dataset of bad driving behavior may not be sufficient to cover all possible scenarios and behaviors, resulting in limited generalization ability of the model. Zhang et al. [13] proposed a method for identifying bad driving behaviors on urban road sections based on class spacing optimization, which collects video data captured by urban road monitoring cameras. These data should include various bad driving behaviors, such as speeding, running red lights, and changing lanes illegally. Preprocess the data, including denoising, cropping, scaling, etc., to facilitate subsequent feature extraction and model training. Extract features from video frames, design a random forest classification model to optimize the categories of different bad driving behaviors, use the extracted features and optimized class spacing to train the random forest classification model, and output the recognition results of bad driving behaviors on urban road sections. This method adds a classifier compared to the previous two methods, effectively improving recognition efficiency. However, there is a risk of overfitting in the class spacing optimization method, which affects the accuracy of recognition results.

In response to the above issues, this article studies a new method for identifying bad driving behaviors on urban road sections, the multi class Adaboost algorithm, which classifies bad driving behaviors on urban road sections to improve recognition efficiency. Through the analysis of bad driving behavior associations, the problem of overfitting is solved, effectively improving the effectiveness and efficiency of identifying bad driving behaviors, and playing an important role in urban road traffic safety.

2. Acquisition of bad driving behavior

2.1. Collection of bad driving behavior

(1) Data collection plan

The experimental research part adopts real vehicle testing, and the entire experiment is divided into five steps: first, environmental information collection, relying on illuminance meters and cameras to collect environmental variables such as illuminance and traffic conditions, Secondly, vehicle data collection relies on CAN-OBD devices, computers, and steering wheel angle sensors to collect and store data streams generated during driving [15], Once again, the collection of physiological information of the driver's heart relies on EEG, eye tracking, and heart rate meters to collect various physiological indicators of the driver during the test process, Then, combine and debug to complete the equipment reliability test for each driver before the test, Finally, collect actual vehicle test data in tunnel group scenarios.

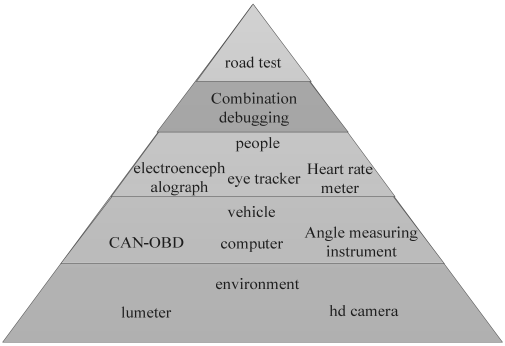

Fig. 1 - Data collection test structure

(a) Driver's work situation (b) Overall information collection process

Fig. 2 - Data collection scenarios

(2) Test equipment

The data acquisition instruments used in this experiment include a contact eye tracker, wireless EEG, heart rate meter, wireless steering wheel angle meter, CAN-OBD, illuminometer, high-definition camera, etc. Before the experiment, adjust the equipment time related to time to be consistent and unify according to "Beijing time", During the experiment, different devices collect data at the same time and space [11].

(3) Test Road

The purpose of the experiment is to study the effect of the operating environment of the tunnel group on the driving behavior of drivers, so the selection of the experimental section should reflect the characteristics of the tunnel group[1]. This article focuses on the study of tunnel groups G in sections A to B of the M expressway. The starting point of the experimental uplink is in the F service area, and the endpoint is at the H toll station.

In order for the data to fully reflect the characteristics of driver behavior, each driver must test once on both the up and down lines, with a total distance of 106km per person. The entire route passes through 19 tunnels, including 1 extra long tunnel, 3 long tunnels, 1 medium long tunnel, and 14 short tunnels[10]. To improve the richness of section sample data, this article divides the tunnel into three sections: entrance section, middle section, and exit section, and expands the research scope of tunnel entrance and exit sections to 100m outside the tunnel. According to the variation law of illumination, the entrance section is composed of 100m before entering the tunnel entrance and 400m after entering the tunnel, the exit section is composed of 400m before and 100m after entering the tunnel entrance, and the rest is the middle section.

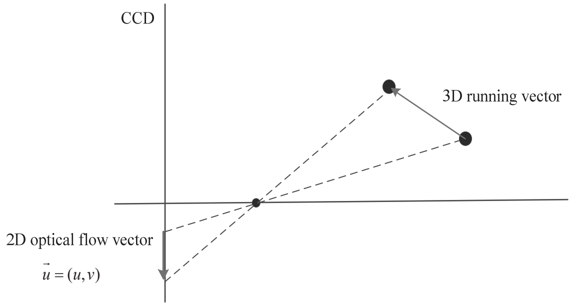

Fig. 3 - Projection optical flow field

2.2. Optical flow image extraction of bad driving behavior

This article uses optical flow diagrams as time information [14, 3] to obtain complete time information as much as possible. The optical flow method is mainly used to describe moving objects in a scene. Generally, object motion can be divided into two types of fields. Firstly, the displacement field of the object in the three-dimensional real world (the change of the object coordinate vector between two consecutive frames) is called the motion field [5]. And its projection on the two-dimensional plane is called the optical flow field, as shown in Figure 3.

The two-dimensional optical flow vector $\vec{u} = (u, v)$ in Figure 3 represents the velocity vector of the current pixel, and the essence of optical flow method is actually to find the velocity vector of each pixel in the image.

Set the brightness of a pixel in a certain frame to $f(x, y, t)$. If after time, the point has moved a distance of (dx, dy), then it can be obtained

$$f(x, y, t) = f(x + dx, y + dy, t + dt) \tag{1}$$

Among them, x, y is the horizontal and vertical coordinates of the point, and t is the time

Expand the Taylor formula on the right half of formula (2):

$$f(x, y, t) = f(x, y, t) + \frac{\delta f}{\delta x}dx + \frac{\delta f}{\delta y}dy + \frac{\delta f}{\delta t}dt \tag{2}$$

Let the remainder of the Taylor expansion be zero, and obtain equation $\frac{\delta f}{\delta x}dx + \frac{\delta f}{\delta y}dy + \frac{\delta f}{\delta t}dt = 0$. Dividing this equation by dt yields the basic optical flow expression:

$$f_x u + f_y v + f_t = 0 \tag{3}$$

wherein, $f_x = \frac{\delta f}{\delta x}; f_y = \frac{\delta f}{\delta y}; u = \frac{dx}{dt}; v\frac{dx}{dt}$。

Similarly, obtain the optical flow formula for the entire image, as shown in formula (4).

$$\min_{u(x,y),v(x,y)} \iint \varphi(T_1(x, y) - T_2(x + u, y + v))\} \tag{4}$$

Among them, $T_1(x, y)$ represents the coordinates of a point in the previous frame of the image, $T_2(x, y)$ represents the coordinates of a point in the current frame of the image, $u(x, y)$ and $v(x, y)$ represent the offset of the point, $\varphi(x)$ represents the error function, generally using a quadratic function [2].

Under the assumption that the rate of change of object motion velocity in the optical flow field tends to zero, a global optimization equation is proposed by incorporating the regularization paradigm:

$$\min_{\mathrm{u}}\{\int \Omega\, |\nabla u_1|^2 + |\nabla u_2|^2 d\Omega + \lambda \int \Omega\, (I_1(x + u(x)) - I_0(x))^2\} \tag{5}$$

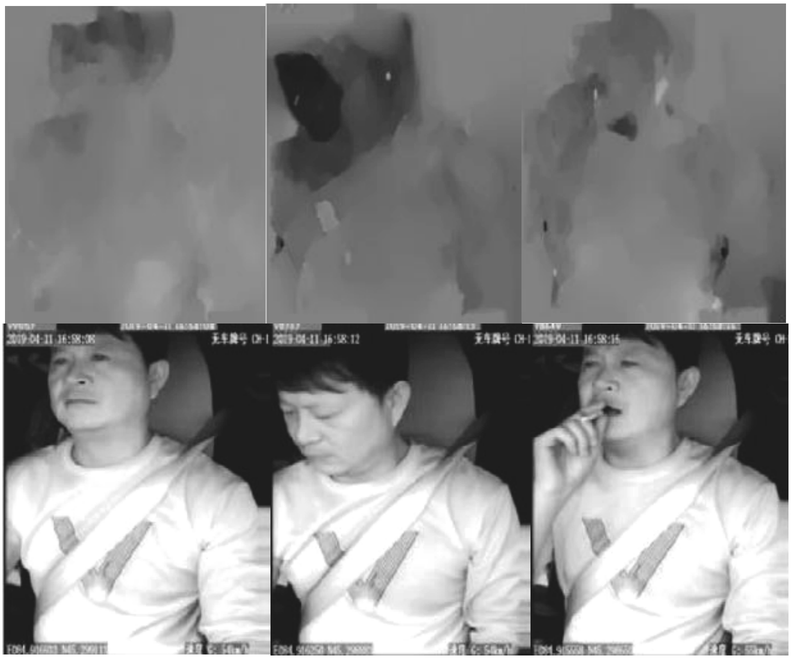

Fig. 4 - Calculation and processing of optical flow method

Here, I_0, I_1 represents the front and back frame images, and $u = (u_1(x), u_2(x))^T$ represents the two-dimensional displacement field of pixels. $\int \Omega \, |\nabla f| = V(f, \Omega)$ represents total variation, usually represented by $\int_a^b |f'(x)| = V_b^a(f)$.

On the basis of formula (5), the TV-L1 optical flow method is proposed, with L1 norm added to maintain the discontinuity of the flow field and enhance the robustness against lighting changes, occlusion, and noise. The objective function is shown below.

$$E(u, v) = \int [\lambda |\rho(v)| + \frac{1}{2\theta}(u - v)^2 + |\nabla u|] \, dx \tag{6}$$

$$\rho(v) = I(x + v_k) + v \nabla I(x + v_k) - T(x) \tag{7}$$

$$\nabla u = |\nabla u_1| + |\nabla u_2| \tag{8}$$

Among them, θ represents a constant, and the value of v approaches u. The TV-L1 optical flow method uses the spiral method for solving. Figure 4 shows the results of optical flow processing on some smoking behaviors in bad driving behavior.

Thus, the image of bad driving behavior calculated and processed by the optical flow method was obtained, completing the acquisition of bad driving behavior.

3. Association recognition of bad driving behavior on urban road sections

3.1. Classification of bad driving behavior based on Adaboost algorithm

The Adaboost algorithm was proposed by Freund and Schapire in 1995, which achieves high classification accuracy without prior training by using different training sets for classification learning. The Adaboost algorithm is a model based on cascaded classification, as shown in Figure 5.

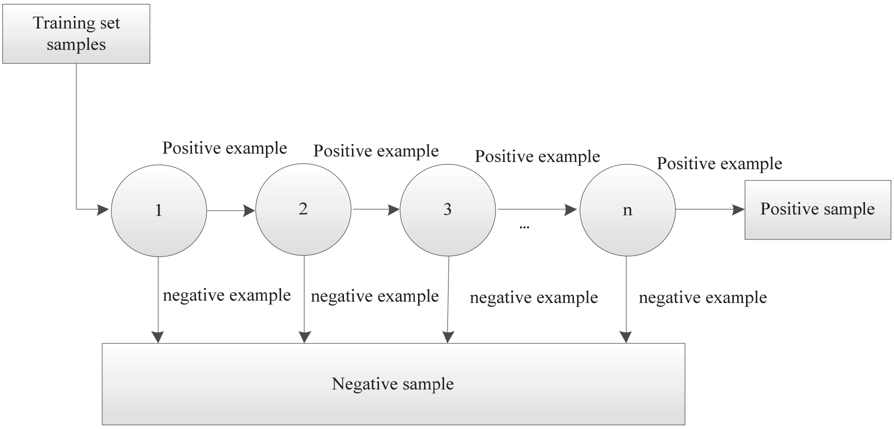

Fig. 5 - Cascade classification algorithm

Detect targets by combining Adaboost algorithm with Haar class features. The main detection method is shown in formula (9).

$$h(x, f, p, \theta) = \begin{cases} 1 & pf(x) < p\theta \\ 0 & other \end{cases} \quad (9)$$

Among them, x represents the detection area, f represents different features, θ is the threshold, p represents the unequal sign to the left or right, and $f(x)$ is the feature value.

The process of training a weak classifier can be as follows. Assuming there is n sample, first calculate the feature value of a rectangular feature in n samples and select feature value f_d as the threshold. So, the sum of the positive sample ratio before the threshold of f_d and the negative sample ratio after the threshold of f_d is μ_1 and μ_2.

For μ_1,μ_2, there is a classification error of e, as shown in formula (10).

$$e = min(\mu_1, \mu_2) \quad (10)$$

When μ_1 is greater than μ_2, it indicates that this weak classifier judges positive samples before the f_d threshold and negative samples after the threshold. When μ_1 is less than μ_2, it indicates that this weak classifier judges positive samples after the f_d threshold and negative samples before the threshold. If the given training sample set is $V = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$, where x_i is the input sample image and y_i is the sample label.

For the $t = (1,2, \dots, T)$th classifier, normalize the weight of each feature value, as shown in equation (11).

$$q_{t,j} = \frac{w_{t,j}}{\sum_{j=1}^{n} w_{t,j}} \quad (12)$$

Among them, $w_{t,j}$ is the jrd feature value of the tnd weak classifier.

Then calculate the weighted error rate ξ_i according to formula (13).

$$\xi_i = \sum_{i=1}^{n} q_t |h(x_i, f, p, \theta) - y_i| \quad (13)$$

Select the h_i with the lowest misjudgment rate as the best classifier ξ_i among the weak classifiers in the current batch, and finally concatenate the best weak classifiers of all batches into a strong classifier $C(x)$ according to a certain rule. As shown in formula (14).

$$C(x) = \begin{cases} 1 & \frac{1}{2}\sum_{t=1}^{T} \alpha_t \leq \sum_{t=1}^{T} \alpha_t h_t(x) \\ 0 & other \end{cases} \quad (14)$$

Among them, $\alpha_t = log\frac{1}{\beta_t} = log\frac{1-\xi_t}{\xi_t} = -log\xi_t$,$T$ are the total training batches.