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# Adaptability of collision warning for motor vehicle drivers: can consciousness recognition improve the warning accuracy?

T. Zhang<sup>1,2</sup> H. Wang<sup>1</sup> S. Patnaik<sup>3</sup>

<sup>1</sup>*College of Mechanical Engineering and Automation, Northeastern University, Shenyang 110819, China*

<sup>2</sup>*College of Applied Technology, Shenyang University, Shenyang 110044, China*

<sup>3</sup>*Department of Computer Science and Engineering, SOA University, Bhubaneswar 751030, India*

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## Abstract

Aiming at the problems of poor risk identification ability and high false alarm rate in current vehicle collision warning technology, the self-adaptability of vehicle driver collision warning is proposed: Can consciousness recognition improve the warning accuracy? Construct an adaptive collision warning model, and quantify the impact of each vehicle's collision with an adaptive weight distribution method. The collision speed, the collision safety factor and the lateral offset related to the collision process are used as the weight distribution index to calibrate the model parameters. The maximum similarity recursive algorithm is used to estimate the characteristics of the current vehicle driving state. The maximum braking deceleration threshold is used to determine the degree of collision risk between the own vehicle and the following vehicle. The collision risk levels of the two workshops are divided into three levels: safety, critical value, and danger. The signal detection principle is adopted to modularize the initial information of the collision warning system, and the driving state assessment threshold adaptation category of the collision warning system is alarmed according to the actual situation. Experiments have verified that when the vehicle collision risk level is the critical value, the DR value of the model in this paper is 0.06 larger than the value of the NCM model, and it takes 3s-6s more time for the driver to take anti-collision and obstacle avoidance measures. Compared with the area under the ROC curve of the NCM model, the local algorithm has high warning accuracy and low false alarm rate.

*Keywords - adaptive model, collision model, maximum similarity, recursive algorithm, threshold optimization*

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## 1. Introduction

Motor vehicles are prone to collision accidents in the process of driving [14]. According to the research, 28% of traffic accidents are caused by improper lane changing operation, and 92% of traffic accidents are caused by driver awareness identification errors. Therefore, the effectiveness of driver awareness identification has a very serious impact on driving safety [18]. In order to improve the safety of motor vehicle driving [17], it can be carried out by improving the driver's awareness identification, so the driver's awareness identification and motor vehicle collision warning technology are the core topics to avoid the problem of motor vehicle collision [15].

In Zhang et al. [19], a vehicle collision warning model based on collision point is proposed. Aiming at the vehicle collision phenomenon at the intersection, different collision scenarios are analyzed under the control of traffic lights, and the estimation methods of collision point location and vehicle arrival time are given. According to the estimation results, a non adaptive collision warning model is constructed. However, the model has the problem of low warning accuracy. In

Wang et al. [10], a vehicle collision warning model based on driving intention sharing is proposed. The model constructs an outfield V2V environment, describes the vehicle driving process as a time series hidden Markov random process, constructs the relationship expression between the driver's intention and the vehicle relative driving state series, and uses Viterbi algorithm to predict the driver's driving intention, according to the prediction results, a non adaptive collision warning model is constructed. However, the early warning effect of the model is not ideal. Wang et al. [11] proposed a vehicle collision early warning model based on game theory combination weighting TOPSIS method. The model constructs a multi-level comprehensive evaluation system of vehicle collision risk situation with "person vehicle road environment" coordination. Delphi method and entropy weight method are used to determine the weight of evaluation index. The optimal balance solution between the weights of selected criteria is obtained by game theory method to complete vehicle collision early warning. However, the early warning efficiency of this model is low.

In order to solve the problems of the traditional non adaptive model, this paper studies the adaptability of collision warning for motor vehicle drivers: can consciousness recognition improve the warning accuracy? In order to provide a theoretical basis for improving the effectiveness of collision warning.

## 2. Parameter optimization of adaptive collision warning model

Combined with the driving situation of surrounding vehicles, the driving risk of the vehicle in the collision process is comprehensively evaluated, and multiple weight quantitative indicators of vehicle impact are input into the model to adapt to the weight distribution to calibrate the collision parameters. In addition, to build and realize the adaptive collision warning model, the driver's consciousness recognition behavior is also needed for online recognition [1].

### 2.1. Adaptive collision warning model

In this paper, a collision scene is simulated in the fast road environment, and the scene is shown in Figure 1.

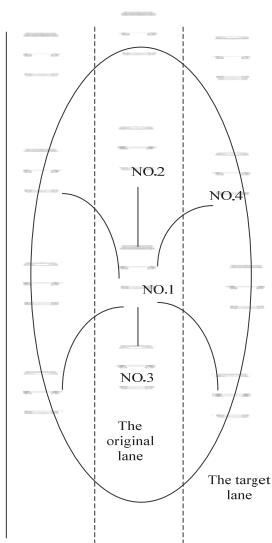


Fig. 1 - Anti collision and lane changing operation of self driving vehicle

When there is a risk of collision, No. 1 motor vehicle (self driving vehicle) turns from the original motor vehicle lane into the target lane, No. 2 motor vehicle and No. 3 motor vehicle represent the front and rear vehicles on the target lane respectively, and No. 4 motor vehicle enters the target lane. The carriageway represents the car in front, and car 5 represents the car behind the target lane. The distance between the front vehicle and the rear vehicle is used to judge whether to turn from the current lane to the target lane. The information exchange of collision process is realized through the network environment of motor vehicles, and the state parameters of motor vehicles are obtained by referring to their own vehicles. Assuming that the self-driving vehicle maintains a certain safe distance from the vehicle in front, using the spring theory, the expected value of the driver's acceleration in the fast lane can be obtained:

$$asv(t) = h, [D1(t) - D(t)] + v(t) - v1(t) \quad (1)$$

where  $D(t)$  represents the ideal distance between the self driving vehicle and the vehicle in front,  $D1(t)$  represents the actual distance between the self driving vehicle and the vehicle in front at time  $t$ ,  $k$  represents the spring coefficient,  $h$  represents the mass of the motor vehicle, and  $L$  represents the damping coefficient;  $v1(t)$  is the relative speed between vehicles at  $t$  time [12].

In addition, a certain amount of turbulence will also be formed in the traffic flow, which will affect the distance between motor vehicles. Based on this condition, the influence of the speed difference between the workshops on the driver's consciousness recognition ability is calculated as:

$$a(t) = k[v(AX(t) - u(i)] + h[v(t) - vn - (t)] \quad (2)$$

where  $a(t)$  is the expected value of longitudinal acceleration; The coordinate and driving speed of the  $n$ th vehicle are represented by  $x(t)$  and  $v(t)$  respectively;  $\Delta X(t)$  is the distance between the front motor vehicle and the rear motor vehicle;  $v(AX(t))$  is the best driving speed of the vehicle;  $h$  and  $k$  are used to represent the accident response coefficient of the driver [8].

When simulating the control of driver awareness identification ability, the expected acceleration mode is adopted. Through the comprehensive analysis of the full speed model and the virtual spring theory model, it is proved that the identification behavior of the driver during the operation has a direct relationship with the driving speed of the driving vehicle [7]. The vehicle speed, safety distance and the value of obstacle avoidance and collision avoidance time can directly reflect the distance and speed of motor vehicles [16]. At the same time, the parameters can also feedback the driver's awareness recognition form and the driving state of the vehicle. Based on this, the ideal acceleration control model is obtained as follows:

$$a_{sv}^*(t) = k_r \cdot u_{sv} [THW(t) - THW^*(t)] + k_v \cdot u_{sv} \cdot THW(t)TTCi(t) \quad (3)$$

where  $THW(t)$  is the ratio of the distance between the self driving vehicle and the front driving vehicle to the vehicle speed,  $TTCi(t)$  is the ratio of the obstacle avoidance time to the distance between vehicles at the current speed, and  $THW^*(t)$  is the safe distance of the motor workshop.

A collision accident is a random behavior. In order to study the obstacle avoidance and collision avoidance problems of driving vehicles, it is necessary to start with parameters such as the trajectory of the motor vehicle, the distance between vehicles, and the obstacle avoidance and collision avoidance time [20]. According to the above parameters, the collision process between motor vehicles and the anti-collision measures for changing lanes are simulated. In addition, tracking is required. The impact of a self-driving vehicle entering the target lane after avoiding obstacles can be derived from the distance  $THW_r$  between the self-driving vehicle and the following vehicle and the obstacle avoidance time  $THW_r$  of the following vehicle:

$$\begin{cases} THW_r = \frac{-d}{-u_{sv}} = \frac{d}{u_{sv}} \\ TTCi_r = \frac{[-u_{sv} - (-u_{fv})]}{-d} = \frac{u_{fv} - u_{sv}}{-d} \end{cases} \quad (4)$$

where  $d$  is the actual distance between the self driving vehicle and the rear motor vehicle.

In this paper, combined with the driving state information of the surrounding vehicles on the way of the self-driving vehicle, considering the driving speed of the own vehicle, the expected acceleration model is improved for collision warning. The collision warning model is  $DR(i)$ :

$$DR(i) = h_\beta [THW(i) - THW_d] + h_\mu \cdot THW(i) \cdot TTCi(i) \quad (5)$$

where  $DR$  is the vehicle collision risk coefficient, which is directly proportional to the current self driving vehicle collision risk [9].  $i$  is the driver's consciousness identification coefficient when the time sample is 0.1s, where  $h_\beta$  and  $h_\mu$  reflect the driver's left and right lane changing operation after consciousness identification.

## 2.2. Collision parameter calibration

Considering the traffic conditions of multi-lane vehicles and vehicles in the target lane, in the same time collision environment, an adaptive weight distribution method is used to quantify the impact of each vehicle's collision [2]. The collision speed, the collision safety factor and the lateral offset related to the collision process are used as the weight distribution indicators, and weight,  $THW$  and  $TTCi$  are used as the calibration parameters, and they are respectively calibrated to obtain,  $\widehat{THW}(i)$  and  $\widehat{TTCi}(i)$ :

$$\begin{cases} \widehat{THW}(i) = \sum_k THW_k \cdot \rho_k \\ \widehat{TTCi}(i) = \sum_k TTCi_k \cdot \rho_k \end{cases} \quad (6)$$

where  $K = LV, ALV, AFV$ ,  $\rho_k$  is the weight factor.

Fuzzy logic method can simulate human brain to make fuzzy judgment on collision concept. This method is the embodiment of modern artificial intelligence technology and can be used to adjust the control parameters of the system [3]. The model has three input indexes and three output indexes.

(1) The driving speed correlation degree of motor vehicles, that is, the grey correlation degree between the relative speed of collision vehicles and the relative speed of surrounding vehicles, is used to describe the driving safety between vehicles. In the theory of grey correlation analysis, collision parameters are standardized, difference sequence, extremum and incidence matrix are generated. The correlation coefficient  $g_k(i)$  is calculated as follows:

$$g_k(i) = \frac{\min_k \min_i A_k(i) + \rho \max_k \max_i A_k(i)}{A_k(i) + \rho \max_k \max_i A_k(i)} \quad (7)$$

where (7),  $\rho$  is the recognition coefficient, when  $\rho=0.5$ , the similarity  $\gamma$  is:

$$\gamma = \frac{1}{n} \sum_{i=1}^n g_k(i) \quad (8)$$

The standard value of the correlation degree of motor vehicle speed can be divided into three levels: low, average and highest. It represents the low, medium and high speed correlation degree of surrounding vehicles and self driving vehicles respectively [4].

(2) Lateral offset refers to the inconsistency of the lateral position when the vehicle collides with surrounding vehicles, and it is directly affected by the driver's operation. For example, when the preceding vehicle collides with a self-driving vehicle, the impact of the collision of the preceding vehicle on the self-driving vehicle weakens as the lateral displacement increases [5].

$$\text{offset}(i) = P_{sv}(i) - P_t(i) \tag{9}$$

where  $t(i)$  is the position of the vehicle in lateral driving, and  $t \in [LV, AFV, ALV]$ . The standard values of lateral offset are near, middle and far, corresponding to the near, middle and far of the direction finding cheapness of the surrounding lateral vehicles and self driving vehicles [13].

(3) Collision safety factor, that is, the ratio of the actual distance between the self-driving vehicle and the surrounding vehicles to the ideal distance. Based on this, the longitudinal safety distance between the self-driving vehicle and the surrounding vehicles is obtained, and the collision safety factor  $s$  is:

$$\varphi_s = \frac{d_o}{d_{\text{safe}}} \tag{10}$$

where  $d_o$  represents the actual longitudinal distance between the self driving vehicle and the surrounding vehicles, and  $d_{\text{safe}}$  represents the critical value of the safe distance between the self driving vehicle and the surrounding vehicles. After a self driving vehicle changes lanes to avoid obstacles, the safety distance between the vehicle and the target lane is determined by  $d_{\text{safe}}$  in the same way [6]. According to the value of collision coefficient, the collision risk is divided into three levels: high, medium and low, and the risk level is inversely proportional to the degree of safety. Gauss function is used to express the collision level:

$$f = (x, \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{11}$$

where (11),  $\sigma$  and  $c$  are real numbers. According to the theory of fuzzy entropy, it can be divided into five grades: maximum value, large value, medium value, small value and minimum value. The output is shown in Figure 2.

### 2.3. Recursive optimization of model parameters

In order to improve the recognition ability of driver's collision awareness, the maximum similarity recursive algorithm with light calculation and good real-time ability is used.

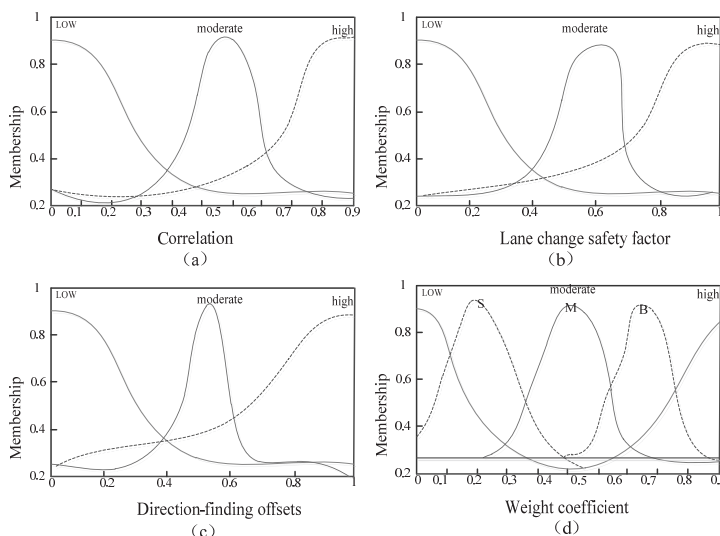


Fig. 2 - Membership function curve

In order to reduce the impact of outdated data in the database on the current vehicle driving state evaluation, the forgetting coefficient iteration method is introduced to make the evaluation value more consistent with the current vehicle driving state characteristics. The linear difference equation is used to describe the system model as follows:

$$y(k) = -a_1y(k-1) - \dots - a_ny(k-n) + b_0u(k) + \dots + b_nu(k-n) + \varepsilon(k) \quad (12)$$

The sequence range in formula (12) is from  $a_1$  to  $a_n$  and  $b_0$  to  $b_n$ , the length of the sequence is  $n$ , and the Gaussian sequence range is  $\varepsilon(k) \sim N(\mu)$ . Based on this, the calculation of the observed values of the eigenparameter vector of the model is described as follows:

$$Y = \varphi\theta + e \quad (13)$$

where the input value of the system is represented by  $\varphi$ ; Then  $\theta$  is the vector to be evaluated;  $e$  is the Gaussian noise when the expected value is 0. After inputting the parameters into the collision warning model in formula (5), the following results can be obtained:

$$\begin{cases} Y(k) = DR(k) = \frac{a(k)}{v(k)} \\ \varphi(k) = [T\hat{H}W(k) - 1T\hat{H}W(k) \cdot T\hat{T}Ci(k)] \\ \theta = [h_\beta \cdot h_\mu + THW_d] \end{cases} \quad (14)$$

Expressed by the similarity function as:

$$L = P(e|\theta, \sigma^2) = (2\pi\sigma^2)^{-\frac{N}{2}} \exp\left\{-\frac{1}{2\sigma^2}(Y - \varphi\theta)\right\} \quad (15)$$

where the variance of the sequence  $\varepsilon(k)$  is denoted by  $\sigma$ . According to the principle of maximum similarity, under the premise of  $f=0$ , the partial derivative of the relevant parameter in formula (15) is calculated to obtain the maximum similarity value of the parameter  $\theta$ :

$$\hat{\theta}_{ML} = (\varphi^T Y) \quad (16)$$

According to the maximum similarity recursive algorithm, according to the increase of the number of observations, and increase the number of recursion of the model, the process is as follows:

$$\begin{cases} \hat{\theta}(k) = \hat{\theta}(k-1) + G(k)\hat{v}(k) \\ G(k) = P(K-1)\varphi(k) \cdot [I + \varphi(k)P(K-1)\varphi(k)]^{T-1} \\ P(k) = [I - G(k)\varphi(k)P(K-1)\varphi] \end{cases} \quad (17)$$

where the maximum similarity estimation value of each parameter at time  $K$  of the model synchronization is  $\hat{\theta}(k)$ ; the prediction error value is represented by  $v(k)$ ; the number of iterations of the posterior estimated mean square error  $P(k)$  of the gain matrix  $G(k)$  at time  $K$  is  $m$ , and the identity matrix is set. When it is  $P$ , the forgetting factor  $\gamma$  takes a value of 0.95. The minimum similarity is  $\varepsilon$ , and the recursive termination condition is that the model contains 3 or more parameter values without change, then the global optimal solution of the algorithm is obtained:

$$\Delta m = \max(\Delta\theta(k) = \frac{\theta(k) - \theta(k-1)}{\theta(k)} < \epsilon | \theta \in \{h_\beta, h_\mu, THW_d\}) \quad (18)$$

### 3. Early warning classification

#### 3.1. Early warning level setting

By observing the driver's operation of self driving vehicle and rear vehicle, we can judge whether self driving vehicle needs lane changing operation to achieve the purpose of obstacle avoidance.



Tab. 1 - Classification of collision risk

Driving state of own vehicle and rear vehicle	Maximum braking deceleration /(m.s <sup>-2</sup> )
Safety	>-1
Threshold value	(-3,1)
Danger	<-3

When driving on the fast lane, the collision risk of motor vehicles is mainly limited by the maximum braking deceleration value. If the rear vehicle keeps moving at a constant speed or the distance between the rear vehicle and the self driving vehicle is within a safe range after accelerating, it means that the risk of collision between the self driving vehicle and the rear vehicle is small, and the driving state of the vehicle is relatively safe. On the contrary, it indicates that there is a risk of collision between self driving vehicle and rear vehicle, which is more dangerous. In this paper, the maximum braking deceleration value is used to judge the degree of collision risk between the vehicle and the rear vehicle. The classification of collision risk of the two workshops is shown in Table 1.

The risk perception value of each state is stored in the database in real time, but the confusion of the sample category will also deepen as the number of samples increases. Before introducing information entropy theory to generate more accurate warning thresholds, the applicability of data characteristics must be described. Information entropy is used to describe the order of sample information categories. The larger the entropy value, the more confusing the information categories collected. On the contrary, the sample classification is more orderly. Early warning threshold information entropy:

$$\text{Entr}(X) = -\sum_{i=1}^k P(D_i, X)\log_2(P(D_i, X)) \tag{19}$$

where (19),  $D_i = \{D_1, D_2, \dots, D_k\}$  represents the characteristic attribute of the driving vehicle, and  $K=3$ .  $K$  is the three grades of judgment result, which are safety, critical value and danger. The ratio between the data classification interval of the judged data  $D_i$  and the overall data category  $X$  is  $P(D_i, X)$ .

$DR_s$  represents the dangerous state value, and its interval feature takes the value range  $C_i = \{C_1, C_2, \dots, C_n\}$ . The maximum similarity algorithm is used to obtain  $C_i'$  as the optimal division value of the chaotic data category  $C_i$ . In the selected interval, the spare critical point  $P$  is divided, and the overall data is trained into three categories of  $S_1, S_2$  and  $S_3$  through the parameter categories, and the weighted average value of the corresponding information entropy  $S_j$  is:

$$E(C, P, S) = \sum_{j=1}^3 \frac{|S_j|}{S} \text{Entr}(S_j) \tag{20}$$

Converge all candidate partition points into the same interval, find the minimum critical value, and obtain the optimal early warning threshold after weighting the optimal partition point:

$$DR_s = C_i(P^*) \tag{21}$$

When the optimal warning threshold  $DR(i) \in DR_s$ , the vehicle collision risk level is critical, and the system enters the primary warning mode; When  $DR(i) < DR_s$ , the vehicle collision risk level is dangerous, and the system enters the advanced warning mode. When  $DR(i) > DR_s$ , the risk level of vehicle collision is safety.

### 3.2. Adaptive threshold adaptation

In this paper, the principle of signal detection is used to modularize the initial information of collision warning system. According to the actual situation, the traffic condition evaluation threshold of the collision early warning system is applied to alarm. See Table 2 for details.

Tab. 2 - Risk assessment and early warning of change track

Lane change status	Failed to warn	Warned
Danger	4	3
Safety	2	1

According to the analysis in Table 2, it can be seen that the data of category 1 and category 4 are classified respectively, and the alarm system will fail to report and trigger errors, that is, when the actual situation is lane change in normal driving, the system will give an alarm. When the actual situation exists collision risk, the system does not alarm. If the two situations are relatively high and beyond the tolerance range of the driver to the collision warning model, it indicates that the current threshold is unreasonable and will reduce the driver's experience of using the system.

Adding new data in the database in real time and deleting invalid data at the same time improve the reliability of data samples and enhance the ability of searching and judging the best threshold. If the frequency of missed and false positives exceeds the threshold, the system will search the optimal threshold again based on the existing database, usually 8%.

**4. Experimental verification**

In order to verify the practical application effect of the research method, the comparative verification experiment was carried out. Install the system into the self driving vehicle and capture 500 groups of driving collision data. The test scenario is shown in Figure 3. In order to test the performance of the algorithm, this paper designs the vehicle collision test in the real environment, and the test section is shown in Figure 4. Select ten drivers to operate the system. The test equipment includes: driving record, speedometer, steering sensor, radar, GPS, etc. The categories of vehicle driving data capture include: driving steering angle, vehicle speed, brake valve opening and closing degree, etc.



The car scenario  
(a)



Driving Forward Scenes  
(b)

Fig. 3 - Test scenario map



Fig. 4 - Test section

The system is embedded in the flat disk computer, and USB link is used to test the AIS system of the vehicle, so as to realize the synchronous input and output of the instrument grabbing data and the vehicle collision data. According to the above experimental data and experimental environment, with the goal of improving the effectiveness of the experiment and reducing the error of the experimental results, the experimental plan is set: the effectiveness of the collision model, the hazard perception sequence value, the collision risk recognition rate, and the driver awareness recognition accuracy rate ( ROC curve) is used as an experimental comparison index to compare and verify the non-adaptive collision model (NCM) of Zhang et al. [19] with the adaptive collision model (ACM) of this paper.

#### 4.1. Collision model validity test

To test the effectiveness of the proposed collision warning model, the acceleration prediction value of the self driving vehicle is obtained in the collision risk assessment model, and compared with the actual value to obtain the driver's awareness identification characteristics in driving operation. The acceleration prediction curve is shown in Figure 5. It can be seen from Figure 5 that the acceleration prediction value identified by the adaptive driver awareness conforms to the operation characteristics of the driver in the actual collision process, which indicates that the model can effectively warn the dangerous collision situation.

#### 4.2. Risk perception sequence value test

The collected data are filtered and classified, and the classified data is input into the collision warning model studied in this paper to obtain the latest parameters of real-time vehicle distance, obstacle avoidance time and current driving state. The DR curve of the sample series is shown in Figure 6.

The optimal segmentation point of data risk level is calculated by the model, and the critical value range is DR [-0.008, 0.0576]. When the DR value is less than -0.008, the collision risk level of motor vehicles belongs to danger. When the DR value is greater than 0.0576, the collision risk level of motor vehicles belongs to safety.

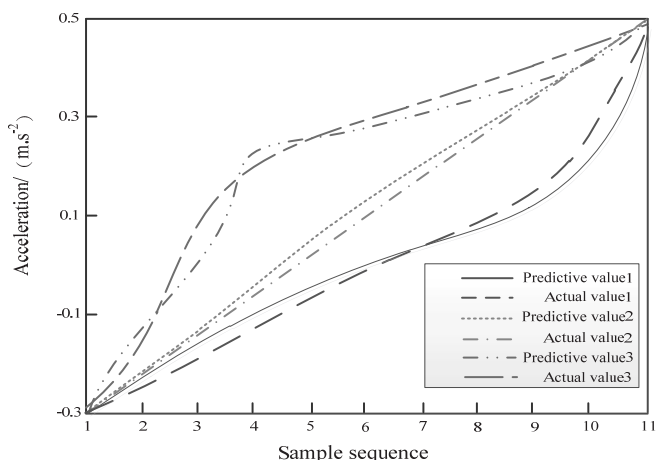


Fig. 5 - Acceleration prediction curve

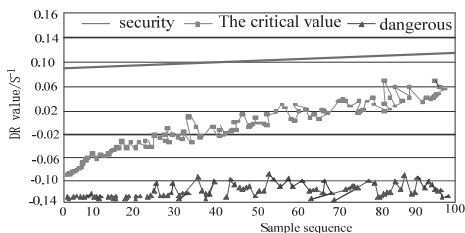
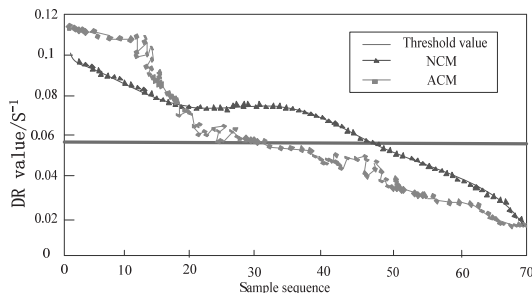
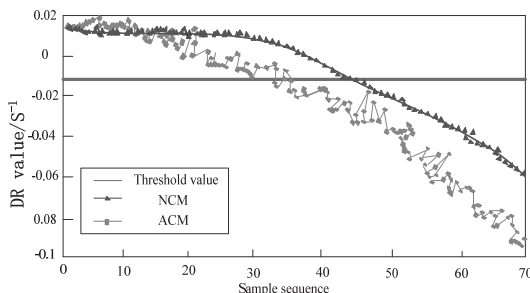


Fig. 6 - DR curve of sample sequence



(a) DR curves of two models at critical values



(b) DR curves of two models in the dangerous state

Fig. 7 - Comparison of DR sequence curves

In order to verify the obstacle avoidance and collision avoidance capabilities of the model in this paper, a non-adaptive collision model (NCM) is used to compare the sequence value of hazard perception with the adaptive collision model (ACM) in this paper. The result is shown in Figure 7. According to Figure 7, in the same sample environment, as the number of samples increases, the risk perception curves of the model in this paper and the NCM model both decline. When the vehicle collision risk level is the critical value, the DR value of the model in this paper is 0.06 larger than the value of the NCM model. It can be seen that the model in this paper buys 3s-6s more time for the driver to take measures to avoid collision and avoid obstacles.

#### 4.3. Collision risk identification rate test

Grabbing 500 sets of vehicle driving state data, using this model and NCM model for state detection, observing the false alarm rate of the two models and the perception ability of the three risk levels. The results are shown in Table 3.

Tab. 3 - Collision risk identification rate (%)

Model name	Test items			
	Safety grade identification rate	Critical value identification rate	Hazard level identification rate	False positives
ACM	88.5	90.2	98.9	0.3%
NCM	73.6	77.1	87.6	2%

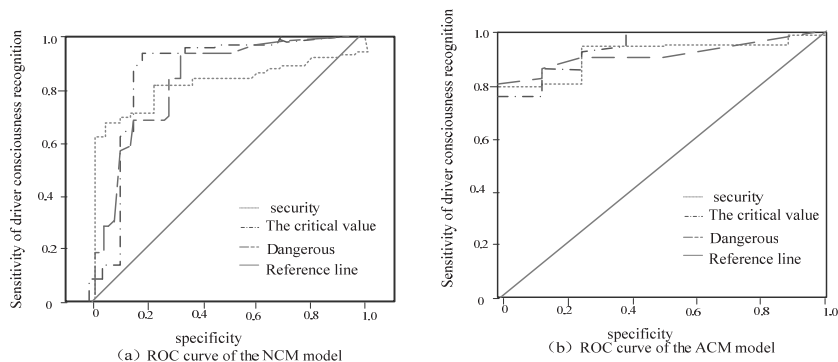


Fig. 8 - ROC curve comparison

It can be seen from Table 3 that the identification rate of this model is higher than that of NCM model in three aspects of safety level identification rate, critical value identification rate and risk level identification rate, and the lowest false alarm rate of this method is only 0.3%, which is far lower than 2% of NCM model.

#### 4.4. Driver awareness recognition accuracy (ROC curve) test

Link the model in this article with the NCM model in Matlab Simhydraulic software, and output the driver's awareness recognition (ROC) curve to judge the accuracy of the model's early warning. In the ROC curve, the larger the area under the curve, the better the algorithm performance and the higher the warning accuracy rate. The ROC curve of the model in this paper and the NCM model is shown in Figure 8. According to Figure 8(a), the AUC values corresponding to the three vehicle collision risk levels in the ROC curve of the NCM model are AUC1=0.818 (safety level), AUC2=0.836 (critical value) and AUC3=0.865 (risk level). According to Figure 8(b), the AUC values corresponding to the three vehicle collision risk levels in the ROC curve of the ACM model are AUC1=0.913 (safety level), AUC2=0.883 (critical value) and AUC3=0.894 (dangerous level). Since the larger the area under the curve, the better the algorithm performance and the lower the false alarm rate. It can be seen that compared with the NCM model, the model in this paper has higher pre-warning accuracy and lower false alarm rate.

### 5. Conclusion

Aiming at the problems of poor risk identification ability and high false alarm rate in current vehicle collision early warning technology, this paper discusses the adaptability of vehicle driver collision early warning: can consciousness identification improve the early warning accuracy? After a series of studies, the adaptive collision model constructed in this paper can effectively warn the collision risk of motor vehicles in the process of driving. Collision speed, collision safety factor and offset as collision risk assessment parameters can effectively evaluate the collision risk level of motor vehicles in the process of driving. The maximum similarity recursive

algorithm has the characteristics of lightweight and good real-time ability in evaluating the maximum braking deceleration threshold to judge the collision risk between the vehicle and the rear vehicle. When the vehicle collision risk level is the critical value, the Dr value of the model in this paper is 0.06 higher than that of the NCM model, which takes more 3s-6s for the driver to take anti-collision measures. Therefore, this study proves that awareness recognition can improve the early warning, buy time for the driver's collision avoidance, and improve the driving safety.

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## Economic evaluation method of traffic safety emergency project based on accident reduction coefficient

L. Zhou<sup>1</sup>      N. He<sup>2</sup>      J. Wang<sup>1</sup>      F. Xue<sup>3</sup>      S. Dissanayake<sup>4</sup>

<sup>1</sup> *Beijing Polytechnic, Beijing 100176, China*

<sup>2</sup> *Beijing Mass Transit Railway Operation CORP.LTD., Beijing 100044, China*

<sup>3</sup> *Beijing Municipal Supply and Marketing Institute, Beijing 102400, China*

<sup>4</sup> *College of Engineering, Kansas State University, Manhattan, KS 66506, USA*

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### Abstract

This paper proposes a traffic safety emergency project economic evaluation method based on the accident reduction coefficient. Lay the foundation for economic evaluation by analyzing the components of the traffic safety emergency project; based on this, calculate the accident reduction coefficient in the traffic safety emergency project, and modify it; combine with the constructed fuzzy evaluation model to realize the multiplicity of the traffic safety emergency project Level of economic evaluation. The experimental results show that compared with the traditional method, this method has a lower error value in the evaluation result, the lowest is 2.37, the evaluation time is always less than 2.0s, and the accuracy of the result is as high as 97%, which shows that the method has a high practical value.

*Keywords - accident reduction coefficient, traffic safety, economic evaluation, fuzzy evaluation model*

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### 1. Introduction

In the context of the continuous development of economic construction, the problem of transportation construction appears to be particularly important, and various transportation tools have been fully utilized. In this context, although the transportation capacity has been greatly improved, some safety hazards have also arisen with it [14, 5]. According to relevant statistics, in recent years, the number of traffic safety accidents has increased year by year, and traffic safety problems are facing serious threats. Although the relevant departments have established a traffic safety early warning mechanism and a traffic emergency response platform, only regulating the macro and organizational structure level cannot fundamentally improve the emergency response effect of traffic safety accidents [12, 6]. Therefore, it is necessary to carry out economic evaluation of traffic safety emergency projects, so as to provide a theoretical basis for the construction of emergency projects, and efficient economic evaluation methods can help ensure the implementation effects of emergency projects. In addition, accurate economic evaluation of traffic safety emergency projects can improve the efficiency of traffic accident handling to a certain extent, and improving the accuracy and feasibility of economic evaluation is an important content of the decision-making of traffic safety emergency projects, thereby effectively improving road traffic safety.

At this stage, domestic and foreign experts and scholars have conducted certain research on traffic safety emergency problems. Among them, foreign research on traffic safety emergency projects mainly focuses on the definition of economic benefits. Domestically, it mainly focuses on vehicle operation speed control, passenger flow scheduling, and passenger flow time. Several

aspects such as management and control have improved the effectiveness of traffic safety management. On this basis, Wang et al. [15] puts forward the economic impact evaluation method of Yinxi high-speed railway construction project. This method mainly starts from the two stages of railway construction and the latter stage of railway operation, and establishes a railway construction project's economic impact evaluation system. In the system, it is mainly composed of traffic conditions, investment effects and other indicators, and the economic benefits of railway construction projects are evaluated using the comparison method and the classical analysis method. The research results show that because the method selects fewer evaluation indicators, it can realize economic evaluation in a relatively short time. However, this method only conducts economic evaluation under normal circumstances, and does not consider the economic benefits of railway construction projects when there are risks, there are problems of incomplete evaluation results and low accuracy of evaluation results. Yu et al. [19] proposes a comprehensive evaluation of regional economy and transportation system development and a comparative analysis method of fitness, using principal component analysis and fitness analysis to evaluate the development of regional economy and transportation. The research results show that the higher the adaptability between the two, the more perfect the transportation structure, but this method only studies the relationship between the two, the research is not comprehensive enough, and the reliability of the data in the research process is not high. This leads to a certain error value in the research results, which affects the development of transportation construction projects. Peng et al. [10] puts forward the evaluation method of county traffic and economic coordination in Poyang Lake area based on raga-ppc model. Firstly, the evaluation index system of economic strength is established. Secondly, the raga-ppc model is used to evaluate the level of traffic and economic development in Poyang Lake area. Finally, combined with the evaluation index system to complete the evaluation of the regional transportation and economic coordination. The research results show that traffic is a key factor restricting local development, but the evaluation index system constructed by this method is more complicated, which leads to a long evaluation time. If it is applied to traffic emergency handling, it will delay emergency handling decision-making.

According to the above analysis, the current method has the problems of error value in the evaluation result, long evaluation time and low accuracy of the evaluation result in the current method of traffic evaluation. For this reason, an economic evaluation method for traffic safety emergency projects based on accident reduction coefficients is designed.

## **2. Economic evaluation method of traffic safety emergency project**

Traffic safety management includes multiple links, of which traffic safety emergency projects are an important part, which can effectively improve the efficiency of traffic accident handling, thereby improving traffic safety [1]. Therefore, it is necessary to optimize the design of economic evaluation methods for traffic safety emergency projects.

### *2.1. Analysis of the composition of the traffic safety emergency project*

The traffic safety emergency project is also composed of multiple links and is a systematic work. It includes traffic safety early warning, traffic safety monitoring, and traffic accident handling before and during the traffic accident, and emergency response after the traffic accident. Accident assessment, accident information archiving, etc. [16]. The processing level of each link has an impact on the processing efficiency of the traffic safety emergency project. Therefore, it is important to accurately grasp each link. The structure of the traffic safety emergency project is shown in Figure 1.



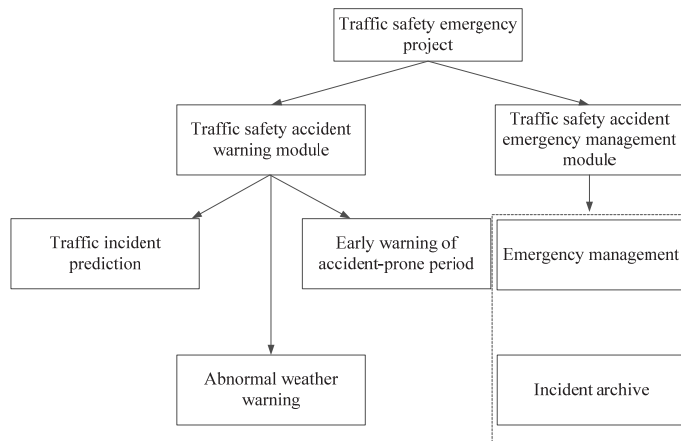


Fig. 1 - Traffic safety emergency project composition

According to Figure 1, the traffic safety emergency project is mainly composed of two sub-modules, namely, a traffic safety accident early warning module and a traffic safety accident emergency management module. Among them, the traffic safety accident early warning module refers to the use of monitoring facilities, monitoring networks and other means to realize the monitoring and early warning of abnormal traffic conditions, so as to provide a time basis for emergency treatment [20]. The traffic safety accident emergency management module means that when a traffic safety accident occurs, effective emergency measures are taken in time to minimize the damage of the accident, so as to minimize the safety risk in the shortest time, so as to restore to the normal traffic operation state. Through the combination of the two modules, the effective control of traffic safety incidents is realized, forming a hierarchical, purposeful and standardized traffic accident emergency project [2].

### 2.2. Overall economic benefits of traffic safety emergency projects

Based on the structure of the traffic safety emergency project, the accident reduction coefficient is used to obtain the reduction coefficient of traffic safety accidents, which provides a data basis for economic evaluation [3]. In order to obtain an accurate accident reduction factor, it is necessary to select an appropriate test site, and then implement traffic improvement measures at this location, and finally conduct accident observations at different times according to the actual situation, so as to obtain the accident reduction factor of the area [17]. In addition, there is a method to obtain the accident reduction coefficient. This method does not require specific field observations. It only needs to propose different observation points for traffic safety emergency improvement measures. The observation points have problems, and the other is There is no problem with the observation point, and then the accident data of the two observation points are obtained through horizontal comparison to obtain the final accident coefficient [8]. Although the second method has the advantage of obtaining data quickly, the accuracy of the obtained data is not high. Therefore, this paper selects the first method to obtain the accident reduction coefficient, which has high data credibility.

In the process of obtaining the accident reduction factor, the average number of accidents before improvement is represented by  $A_1$ , the average number of accidents after improvement is

represented by  $A_2$ , the average traffic volume before improvement is represented by  $B_1$ , and the average traffic volume after improvement is represented by  $B_2$ . The calculation formula for the accident reduction factor is:

$$C = \left[ 1 - \frac{B_1}{\frac{A_1}{A_2} \times B_2} \right] \times C_i \quad (1)$$

where  $C_i$  represents the accident reduction coefficient correction parameter, and its calculation formula is as follows:

$$C_i = \sum_{i=1}^n (x_i \times x_j)^2 \quad (2)$$

where  $n$  represents the number of accidents;  $x_i$  represents the capacity of the road in the accident state;  $x_j$  represents the evacuation time of the accident. Using formula (2) to modify the accident reduction coefficient obtained in formula (1) can reduce the impact of uncertain factors, including the number of accidents, the number of pedestrians, and traffic flow [18].

In order to further enhance the credibility of the accident reduction factor and adapt to traffic changes, the reduction factor is updated [9]. If the reduction factor obtained from formula (1) is set as the old one, the new one is set as  $C'$ , and the calculation formula is as follows:

$$C' = \mu \left[ C_i \times \left( \frac{1}{C} - \frac{1}{C'} \right) - \frac{Z_1}{Z_2} \right] \quad (3)$$

where  $\mu$  represents the information acquisition coefficient of traffic emergency observation points;  $Z_1$  represents the average number of accidents after the update;  $Z_2$  represents the average traffic volume after the update.

The revised accident reduction factor can be obtained by formula (3), but in order to apply it to the economic evaluation of traffic safety emergency project, two preconditions need to be met: the new and old reduction factors are independent; the estimation method of the new and old reduction factors meets the normal distribution condition.

According to the accident reduction coefficient, the traffic safety measures are arranged according to the importance degree, and then the accident reduction coefficient of all traffic safety improvement measures is obtained, including the accident economic loss, traffic reconstruction project cost, safety benefit, etc. By sorting the results [11], dividing by the project cost can obtain the overall economic benefit calculation model of the traffic safety emergency project:

$$S_{ij} = \sum_{k=1}^6 (b_k - \Delta T_k) \quad (4)$$

where  $k$  represents the economic benefits produced by the traffic safety emergency project;  $b_k$  represents a quantifiable index;  $\Delta T_k$  represents the index transformation coefficient under the influence of uncertain factors. Under normal circumstances, a traffic safety emergency project contains 6 quantifiable indicators, and the economic benefit calculation model produced under the combined action of different indicators is:

$$S_{ij} = \sum_{k=1}^6 (b_{1k} + b_{2k} + b_{3k} + b_{4k} + b_{5k} + b_{6k}) \quad (5)$$

where  $b_{1k}$  represents the benefit of improved traffic safety accident;  $b_{2k}$  represents the benefit of energy saving;  $b_{3k}$  represents the benefit of pollution reduction;  $b_{4k}$  represents the benefit of passenger travel time;  $b_{5k}$  represents the benefit of labor production;  $b_{6k}$  represents the benefit of accident handling.

So far, the calculation of the overall economic benefits of the traffic safety emergency project has been completed. On this basis, combined with the accident reduction factor, the economic evaluation of the traffic safety emergency project is realized.

### **3. Realization of economic evaluation of traffic safety emergency project based on accident reduction coefficient**

In the process of economic evaluation of traffic safety emergency projects, the rationality of emergency projects should be evaluated based on the accident reduction coefficient, combined with the principle of reasonable resource allocation, and the economic costs and social resources consumed during the implementation of traffic safety emergency projects. The feasibility and economic value of emergency projects are judged by the following indicators [7].

#### *3.1. Construction of evaluation index system*

The economic evaluation indicators of traffic safety emergency projects mainly include the project's internal economic rate of return, economic net present value, and economic net present value rate. The above indicators are specifically calculated below.

##### (1) Economic internal rate of return

The economic internal rate of return of the traffic safety emergency project mainly reflects the contribution rate of the emergency project to the national, which is an absolute effect index [13]. When determining the traffic safety emergency project, this index is mainly considered, which can be calculated by formula (6)

$$\varpi = \sum_{i,j=1}^n S_{ij} e^{H_i - H_j} \quad (6)$$

where  $S_{ij}$  represents the net cash flow;  $e$  represents the discount rate;  $H_i$  and  $H_j$  represent the cash inflow and outflow, respectively.

##### (2) Economic net present value

The economic net present value of a traffic safety emergency project refers to the sum of the net present value of the emergency project during the emergency cycle using the discount rate. It can reflect the impact of different quantifiable indicators on the national economy. The calculation formula is:

$$\omega = \sqrt{\frac{\sum_{i,j=1}^n (v_i - v_j)^2}{N}} \quad (7)$$

where  $v_i$  represents the estimation of the time value of funds;  $v_j$  represents the increase in financial net present value.

##### (3) Economic net present value rate

The economic net present value rate of the traffic safety emergency project can reflect the contribution rate of the traffic safety emergency project to the economic benefits [4], and its calculation formula is:

$$\vartheta = \left[ \frac{\omega}{b^{(l,s)}} \right] \times 100\% \quad (8)$$

where  $b^{(l,s)}$  represents the present value of investment.

According to the above calculation formula, obtain the evaluation index, complete the construction of the evaluation index system, and use it for the economic evaluation of the traffic safety emergency project.

#### *3.2. Establish an economic evaluation model for traffic safety emergency projects based on the accident reduction coefficient*

A multi-level traffic safety emergency project economic evaluation model is established based on the accident reduction coefficient and the fuzzy evaluation model. The specific implementation

steps are as follows:

First, establish a factor set, where the factor set of the first level is represented by  $Q = \{q_1, q_2, \dots, q_n\}$ , the factor set of the second level is represented by  $Y = \{y_1, y_2, \dots, y_n\}$ , and the factor set of the third level is represented by  $D = \{d_1, d_2, \dots, d_n\}$ .

Secondly, determine the weight set, which can be expressed as:

$$L = \{q_i, y_i, d_i\} \quad (9)$$

where  $q_i$  represents the  $i$ -th factor in the first-level factor concentration;  $y_i$  represents the  $i$ -th factor in the second-level factor concentration;  $d_i$  represents the  $i$ -th factor in the third-level factor concentration.

Establish a model under the fuzzy evaluation standard based on the weight set, and express it in the form of a matrix:

$$H = \begin{bmatrix} h_{11}, h_{12}, \dots, h_{1n} \\ h_{21}, h_{22}, \dots, h_{2n} \\ \vdots \\ h_{n1}, h_{n2}, \dots, h_{nm} \end{bmatrix} \quad (10)$$

where  $h_{nm}$  represents the weight set under the fuzzy evaluation standard.

The economic evaluation of traffic safety emergency projects is carried out on each single factor evaluation criterion in formula (10), and the multi-level evaluation is realized by combining the common evaluation results among multiple factors.

In summary, based on the composition structure of the traffic safety emergency project, the accident reduction coefficient in the traffic safety emergency project is calculated, and the fuzzy evaluation model is obtained according to the calculation result, so as to realize the economic evaluation of the traffic safety emergency project.

#### **4. Experimental analysis**

To verify the effectiveness of this method in the economic evaluation of traffic safety emergency projects as the experimental purpose, the experimental analysis is carried out.

##### *4.1. The overall scheme design of the experiment*

(1) Experimental environment setting: This experiment is carried out in an experimental environment where the hardware conditions are Intel Core i5-1135G7, the graphics card type is NVIDIA MX330, the memory capacity is 16G, the resolution is 1920x1080, and the data processing software is FineBI. Because there are factors such as noise signals and interference data in the experiment that affect the data processing effect, the experimental conditions are set to a non-interference state to ensure the reliability of the experimental results.

(2) Experimental data: Taking the traffic flow data of a certain street in a certain area as the experimental object, the traffic flow data of the studied area is shown in Table 1.

(3) Experimental program setting: Based on the experimental area traffic flow data in Table 1, the literature [15] method, the literature [19] method and the literature [10] method are used as comparison methods to compare the application effects of the traditional method and the method in this paper.

##### *4.2. Experimental index design*

In order to better verify the actual application effect of the method in this paper, the accuracy of the evaluation results, the proportion of the error value in the research results and the evaluation time are used as the experimental indicators.