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The vehicle collision warning on urban road based on internet of vehicles data

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Abstract

It is of great significance to provide early warning for vehicle collisions on urban roads. In order to overcome the high missing rate and low warning accuracy and poor efficiency of traditional early warning methods, an urban road vehicle collision early warning method based on Internet of Vehicles data was proposed. The extended Kalman filter is used to estimate the vehicle attitude on urban roads, and the vehicle longitudinal safety distance model is established. Based on the Internet of Vehicles, the position, speed, acceleration and heading information of follow-up vehicles on urban roads and vehicles in front of urban roads are obtained, and the dispersion of vehicle spacing changes is obtained. The dispersion is used as the judgment threshold of urban road vehicle collision warning to realize collision warning. The experimental results show that the average false alarm rate is 1.2%, the maximum false alarm rate is only 1%, and the alarm time is only 19.9s.

Keywords - internet of vehicles data, kalman filter, urban road, safe distance model, vehicle collision warning

1. Introduction

With the continuous increase of car ownership, reducing the traffic accident rate has become an important issue to be solved urgently in all countries. The rapid development of the automobile industry has put forward higher requirements for traffic safety travel, and improving road traffic safety has become a major issue to be solved urgently [12, 14, 6]. Traffic accidents bring a lot of life and property to human beings every year, and become an important factor affecting people's normal life. The driver's untimely response and improper handling are the main reasons for the occurrence of traffic accidents. Traffic accidents often occur in a short period of time. If we can predict and identify the dangerous state of urban road vehicles and provide early warning information to relevant drivers in advance, we can effectively reduce vehicle collision accidents and improve road traffic safety [7, 9]. Because the vehicle collision warning system is widely distributed, complex in structure, and many scenes, it is easy to cause traffic accidents, and it has become an important topic of current traffic conflict prevention and early warning. Therefore, it is of great significance to provide early warning for vehicle collisions on urban roads.

At present, scholars in related fields have carried out research on vehicle collision warning, and have achieved certain results. Yuan et al. [15] proposed an adaptive vehicle collision warning method based on vehicle driving behavior. Using monocular distance measurement and vehicle detection methods, a forward vehicle collision warning framework is constructed. The parameters of the camera can be calibrated by using three physical points, so as to realize the rapid calibration of the camera. In the previous vehicle detection, a distance-based multi-scale detection method was adopted. In addition, the introduction of abnormal driver behavior makes the vehicle forward collision warning adaptive. The algorithm proposed in this paper is verified by the actual data of the actual scene, and it has certain validity. Gluhaković et al. [2] proposes a vehicle detection method for potential collision warning in an autonomous vehicle environment. The method consists of two parts and is implemented in the robot operating system. The first part is for vehicle detection in an automated vehicle environment, using the YOLO v2 algorithm trained on a newly created set of images. The YOLO v2 algorithm is configured to detect four classes of objects: cars, vans, trucks, and buses. The second part of the method is the robot operating system node for distance evaluation. In particular, two robot operating system nodes are created for distance evaluation. One robot os node is used for distance evaluation in the Kara simulator, while the other robot os node is used for real-world distance evaluation. This method has good results. However, the above methods still have the problems of poor prediction effect, low accuracy and low efficiency.

In view of the above problems, the vehicle collision warning method on urban road based on Internet of Vehicles data is studied. The overall design scheme of this method is as follows:

(1) Based on the Internet of Vehicles data, the characteristics of bad driving behavior of urban road vehicles are extracted. According to the feature extraction results, the extended Kalman filter is used to estimate the pose of urban road vehicles, so as to establish the vehicle longitudinal safety distance model.

(2) Based on the vehicle longitudinal safety distance model and the Internet of Vehicles, obtain the position, speed, acceleration and heading information of the following vehicles on the urban road and the vehicles in front of the urban road, obtain the dispersion of the change of vehicle spacing, and take the dispersion as the judgment threshold of vehicle collision warning on the urban road. Once the value is exceeded, the vehicle collision warning on the urban road needs to be carried out immediately.

(3) Through experiments, the missing rate of urban road vehicle collision early warning, the accuracy and efficiency of urban road vehicle collision early warning are compared.

2. Urban road vehicle collision warning methods

2.1. Extracting the characteristics of bad driving behavior of urban road vehicles

The Internet of Vehicles is a dedicated mobile ad hoc network capable of providing communication between adjacent vehicles and adjacent road facilities. It is based on short-range wireless communication between vehicles [17, 10]. In these networks, each vehicle is equipped with a device with communication, a computing device and a GPS receiver. The GPS receiver is responsible for providing all the information of the vehicle. Such as the speed of the vehicle, the direction of the vehicle's movement, and the time, each vehicle stores information about itself and other vehicles in a local database whose records are regularly broadcast to other vehicles and roadside equipment.

Aiming at the problem of collision warning of urban road vehicles, this paper proposes to use the data of the Internet of Vehicles to obtain the characteristics of drivers' bad driving behavior in the Internet of Vehicles data system. This article focuses on overspeeding, emergency acceleration (deceleration), emergency lane changes, etc.

(1) Speeding: That is, when the driver is driving, the speed exceeds the speed stipulated by laws and regulations. Speeding is a very dangerous driving behavior that not only causes serious traffic accidents, but also endangers the lives of drivers and other drivers. The article takes the proportion of overspeeding time and the proportion of overspeeding times as the research object.

(2) Emergency acceleration (deceleration): Refers to the situation in which the vehicle suddenly accelerates or brakes when starting or running, which is of great significance to the driving safety of the transport vehicle and the safety of the transported goods. Use GPS data to find its instantaneous acceleration, and conduct rapid start and stop through the acceleration for graded evaluation.

(3) Emergency lane change: That is, the motor vehicle suddenly turns to another lane from the original lane. When driving, if the lane is changed suddenly, it is easy to cause the vehicle to rub and rear-end. Sudden lane changes on the highway can lead to serious traffic accidents.

Curvature is the ratio of the moving distance of two positions to their straight-line distance. It can reflect the path curve of two positions, so use the position distance and driving distance of the car to find the curvature, and use the curvature to determine whether it is a sharp lane change, the formula is as follows:

$$s_i = \frac{dist(p_{i-1},p_i)+dist(p_i,p_{i+1})}{dist(p_{i-1},p_{i+1})} \tag{1}$$

where p_i is a sequence of a series of GPS points, p_{i+1} is the last sequence of p_i, and $dist$ is the distance. Through the above analysis, the bad driving behavior characteristics of urban road vehicles can be obtained.

2.2. Pose estimation of vehicles on urban roads

According to the extracted characteristics of bad driving behavior of urban road vehicles, the extended Kalman filter [13, 4, 5] is firstly used to estimate vehicle poses on urban roads.

Firstly, the motion equation of urban road vehicles is listed. The obtained data has six parameters: longitudinal and abscissa coordinates, speed, heading angle, acceleration β and yaw rate. The state matrix of urban road vehicles is Z and the measurement matrix is.

The measurement equation can be obtained from formula (2):

$$X(k) = Z(k) + e(k) \tag{2}$$

where $Z(k)$ represents the observation equation and $e(k)$ represents the error equation.

The state matrix of urban road vehicles at time r_0 is:

$$Z(r_0) = \left(q(r_0)w(r_0)e(r_0)\alpha(r_0)\beta(r_0)\alpha'(r_0)\right)^T \tag{3}$$

The approximate estimated state matrix at time r_1 is $Z'(r_0, r_1)$. When r_0 is small enough, the longitudinal acceleration and yaw angular velocity α' of the urban road vehicle can be replaced by the values at the previous moment, then the state estimation matrix of the urban road vehicle at r_1 is:

$$Z'(r_0,r_1) = \left(q'(r_0,r_1)w'(r_0,r_1)e'(r_0,r_1)\alpha'(r_0,r_1)\beta'(r_0,r_1)\right)^T \tag{4}$$

Therefore, the one-step prediction equation for the state of urban road vehicles can be obtained:

$$Z'_{k|k-1} = \delta'(Z'(k-1|k-1), k-1) \tag{5}$$

where δ' is a constant matrix. Linearize the system equations and obtain the Jacobian matrix [14-15], then $\delta'(k)$ and $\varepsilon'(k)$ are:

$$\delta'(k) = \begin{bmatrix} 1 + Z'_{k|k-1} & 0 \\ 0 & 1 - Z'_{k|k-1} \end{bmatrix} \tag{6}$$

Through the above steps, the pose estimation of the vehicle on the urban road is completed, and the data base is provided for the establishment of the vehicle longitudinal safety distance model.

2.3. Establish a longitudinal safety distance model for urban road vehicles

On the basis of the above-mentioned urban road vehicle pose estimation, a vehicle longitudinal safety distance model is established [16, 8].

Assuming that the initial velocities of the following vehicle and the preceding vehicle on the urban road are e_1 and e_2, respectively, the maximum decelerations of the following vehicle and the preceding vehicle on the urban road are y_1 and y_2, respectively. In the first stage, the urban road follows the vehicle to keep the original speed, the driver's delay time is t_1, and the braking system's delay time is t_2. The distances traveled by urban road vehicles in the first stage are:

$$u_1 = e_1 \times t_1 \tag{7}$$

The driving distance of the second phase is calculated. In the response time of the braking system, the driving distance of the car on the city road can be expressed as:

$$u_2 = e_1 \times (t_1 + t_2) \tag{8}$$

In the third stage, the deceleration of urban road vehicles reaches the maximum value y_1, and urban road vehicles will continue to brake at the maximum deceleration until the urban road vehicles stop completely. The distance traveled by urban road vehicles in the third stage can be expressed as:

$$u_3 = \frac{e_1^2}{2y_1} - \frac{y_1}{24} \times y_2 \tag{9}$$

Through the analysis of the whole braking process of the urban road vehicle, the distance traveled by the urban road vehicle in the whole process can be calculated as:

$$D_1 = u_1 + u_2 + u_3 = e_1 \times t_1 + e_1 \times t_s + \frac{e_1^2}{2y_1} - \frac{y_1}{24} \tag{10}$$

where t_s represents braking parameters.

Since the following vehicle on the city road starts to enter the early warning state when it senses the speed change of the vehicle in front of the city road, the braking process of the vehicle in front of the city road starts from the second stage. Through the above analysis, the braking distance of the vehicle in front of the city road can be calculated as:

$$D_2 = e_2 \times t_s + \frac{e_2^2}{2y_2} \tag{11}$$

In the process of following the vehicle in front of the city road, if the vehicle following the city road suddenly decelerates, the vehicle following the city road needs to make a corresponding braking action. In order to avoid a rear-end collision with the vehicle in front of the urban road, the following vehicle on the urban road needs to maintain a corresponding distance from the vehicle in front of the urban road. Assuming that the distance between the following vehicle on the urban road and the vehicle in front of the urban road is exactly the safe distance, the distance between the following vehicle on the urban road and the vehicle in front of the urban road is defined as the warning critical distance:

$$\mathrm{D_{WAR}} = \mathrm{D_1} \times \mathrm{D_2} + \theta \tag{12}$$

Based on the above analysis, the establishment of the longitudinal safety distance model for urban road vehicles is completed.

2.4. Realization of urban road vehicle collision warning

The Internet of Vehicles is essentially a temporary network, which is created according to the concept of establishing automobile network according to specific needs or situations. At present, the Internet of Vehicles has established a reliable network. Vehicles mainly use the Internet of Vehicles for the purpose of communication in expressway or urban environment. The difference between Internet of Vehicles and mobile ad hoc network lies in the hybrid network architecture, node mobility characteristics and new application scenarios. In the on-board ad hoc network, that is, the data of the Internet of Vehicles, all mobile vehicles are regarded as mobile data nodes, and their distance from each other on the road is regarded as the data edge in the network. Each vehicle can receive and transmit data communicated with other vehicles or road infrastructure through wireless media. On this basis, through the analysis of the data of the Internet of Vehicles, the position coordinates of other vehicles on the urban road based on the vehicle are obtained. Obtain the position, speed, acceleration and heading information of the vehicle following the urban road and the vehicle in front of the urban road, and realize the collision warning of the vehicle on the urban road.

In a certain period of time, it is assumed that the current moment $\mathrm{v_k}$ and the next moment $\mathrm{v_{k+1}} \in (\mathrm{v_m}, \mathrm{v_n})$ are assumed. At time v_k, the coordinate of the vehicle in front of the urban road is $(\mathrm{b_k}, \mathrm{h_k})$, then the distance between the vehicle in front of the urban road and the following vehicle on the urban road at this moment is:

$$d_{v_k} = \sqrt{{b_k}^2 + {h_k}^2} \tag{13}$$

At time $\mathrm{v_{k+1}}$, this time point is still based on the following vehicle on the urban road as the coordinate, the coordinate of the vehicle in front of the urban road is $(\mathrm{b_{k+1}}, \mathrm{h_{k+1}})$, and the distance of the vehicle in front of the urban road is:

$$d_{v_{k+1}} = \sqrt{{b_{k+1}}^2 + {h_{k+1}}^2} \tag{14}$$

In two adjacent moments $\mathrm{v_k}$ and $\mathrm{v_{k+1}}$, the distance change between the vehicle in front of the urban road and the following vehicle on the urban road is:

$$\Delta d = d_{v_{k+1}} - d_{v_k} \tag{15}$$

where d_{v_k} represents the position of the front vehicle and $d_{v_{k+1}}$ represents the position of the following vehicle.

If $\Delta \mathrm{d} < 0$, it means that the following vehicles on the urban road are gradually approaching the vehicles in front of the urban road ahead; If $\Delta \mathrm{d} > 0$, it means that the following vehicles on the urban road are gradually moving away from the vehicles in front of the urban road. Assuming that the update frequency of urban road vehicle information is F, the dispersion of the change in the distance between the following vehicle on the urban road and the front vehicle driving on the urban road in period 111 can be expressed by variance:

$$\mathrm{D}(\Delta \mathrm{d}) = \frac{1}{(\mathrm{v_n} - \mathrm{v_m})\mathrm{F}} \sum_{\mathrm{i}=1}^{(\mathrm{v_n}-\mathrm{v_m})\mathrm{F}} (\Delta \mathrm{D_i} - \overline{\Delta \mathrm{D}})^2 \tag{16}$$

where $\Delta \mathrm{D_i}$ represents the moving speed of the front vehicle and $\overline{\Delta \mathrm{D}}$ represents the moving speed of the following vehicle.

The larger the $\mathrm{D}(\Delta \mathrm{d})$ value, the larger the distance between the following vehicle on the urban road and the preceding vehicle on the urban road. At this time, it is necessary to use the on-board warning system to remind the driver, so that the vehicles on the urban road can drive smoothly, so as to avoid unstable traffic on the urban road.

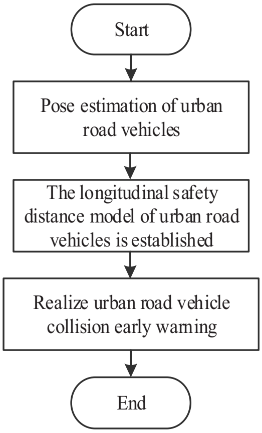

Fig. 1 - Flow chart of vehicle collision warning on urban road

Through the above steps, vehicle collision warning on urban roads can be realized. The urban road vehicle collision warning process is shown in Figure 1.

3. Experimental simulation and analysis

3.1. Set up the experimental environment

In order to verify the effectiveness of vehicle collision warning method on urban road based on Internet of Vehicles data, this paper applies micro traffic simulator VISSIM and network simulator OMNeT++ to build the Internet of Vehicles platform under Linux system. The operating system version is Ubuntu Linux 12.04LST, OMNeT version is OMNeT++ 4.4, SUMO version is SUMO 0.21.0, and venis version is Veins 3.0. Take the vehicle networking data of a city within 3 months as the experimental sample data, and integrate and de reprocess the experimental sample data to ensure the authenticity and reliability of the experimental results. The method of Yuan et al. [15] and Gluhaković et al. [2] and the proposed method are compared to verify the effectiveness of the proposed method. The missing rate of urban road vehicle collision warning, the missing rate of urban road vehicle collision warning, the false alarm rate and the warning time are taken as the evaluation indexes. The specific description of indicators is as follows:

In order to verify the collision warning effect of urban road vehicles by the proposed method, the missing rate is taken as the evaluation index. The lower the missing rate is, the better the collision warning effect of urban road vehicles is. The calculation formula is:

$$\mathrm{L_B} = \frac{\mathrm{L_Y}}{\mathrm{N_Y}} \times 100\% \tag{17}$$

where $\mathrm{L_Y}$ refers to the number of underreported urban road vehicle collision warnings, and $\mathrm{N_Y}$ refers to the random number of urban road vehicle collision warnings.

On this basis, the accuracy of urban road vehicle collision warning of the proposed method is further verified. Taking the false alarm rate as the evaluation index, the lower the false alarm rate, the higher the accuracy of urban road vehicle collision warning. The calculation formula is:

$$\mathrm{W_B} = \frac{\mathrm{W_Y}}{\mathrm{N_Y}} \times 100\% \tag{18}$$

where $\mathrm{W_Y}$ refers to the number of correct urban road vehicle collision warning errors.

Finally, the efficiency of the proposed method is verified. Taking the early warning time as the evaluation index, the shorter the early warning time, the higher the efficiency.

3.2. Comparative analysis of missing rate of collision warning of urban road vehicles

The method of Yuan et al. [15] and Gluhaković et al. [2] are used to compare with the proposed method, respectively, and the comparison results of vehicle collision warning and missed alarm rate of urban road vehicles with different methods are shown in Figure 2.

Analysis of Figure 2 shows that when the number of urban road vehicle collision warnings is 1,000, the average urban road vehicle collision warning missed rate of Yuan et al. [15] is 4.2%. The average urban road vehicle collision warning miss rate of Gluhaković et al. [2] is 7.1%. The average urban road vehicle collision warning miss rate of the proposed method is 1.2%. It can be seen that the urban road vehicle collision early warning rate of the proposed method is low, indicating that the proposed method has a better urban road vehicle collision early warning effect.

3.3. Comparative analysis on false alarm rate of collision warning of urban road vehicles

The method of Yuan et al. [15] and Gluhaković et al. [2] are used to compare with the proposed method respectively, and the comparison results of the false alarm rate of vehicle collision warning on urban roads with different methods are shown in Figure 3.

Analysis of Figure 3 shows that with the increase in the number of urban road vehicle collision warnings, the false alarm rate of urban road vehicle collision warnings with different methods increases. When the number of urban road vehicle collision warnings is 1,000, the false alarm rate of urban road vehicle collision warning by Yuan et al. [15] is 3.8%. The urban road vehicle collision warning false alarm rate of Gluhaković et al. [2] is 5.9%. However, the false alarm rate of vehicle collision warning on urban roads is only 1%. It can be seen that the false alarm rate of urban road vehicle collision warning of the proposed method is low, indicating that the proposed method has a high accuracy of urban road vehicle collision warning.

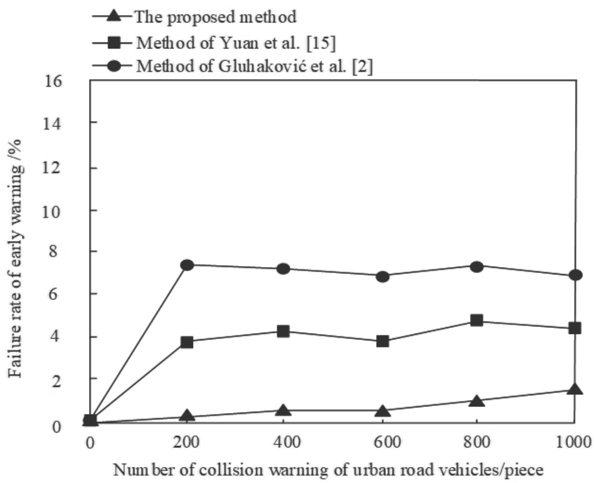

Fig. 2 - Comparison results of vehicle collision early warning and missed reporting rates for different methods on urban roads

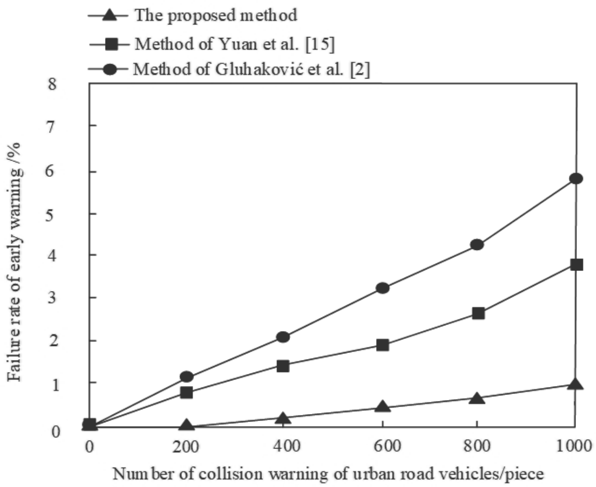

Fig. 3 - Comparison results of the false alarm rate of urban road vehicle collision warning by different methods

3.4. Comparative analysis of collision warning time of urban road vehicles

The method of Yuan et al. [15] and Gluhaković et al. [2] are used to compare with the proposed method respectively, and the comparison results of vehicle collision warning time on urban road with different methods are shown in Table 1.

Analysis of Table 1 shows that with the increase in the number of urban road vehicle collision warnings, the urban road vehicle collision warning time of different methods increases. When the number of urban road vehicle collision warnings is 1000, the urban road vehicle collision warning time of Yuan et al. [15] is 25.6s. The urban road vehicle collision warning time of Gluhaković et al. [2] is 30.2s. However, the vehicle collision warning time of the proposed method is only 19.9s. It can be seen that the proposed method has a shorter early warning time for urban road vehicle collision, and can effectively improve the urban road vehicle collision early warning efficiency.

Tab. 1 - Comparison results of vehicle collision warning time on urban roads with different methods

Number of vehicle collision warnings on urban roads/piece	The proposed method/ms	Method of Yuan et al. [15] /ms	Method of Gluhaković et al. [2] /ms
200	9.8	12.9	15.2
400	11.3	15.7	19.8
600	14.7	18.6	23.9
800	17.2	22.3	26.3
1000	19.9	25.6	30.2

4. Conclusion

This paper studies the vehicle collision warning method on urban road based on Internet of Vehicles data, and carries out early warning of urban road vehicle collision based on Internet of Vehicles data. The experimental results show that the average miss rate of urban road vehicle collision early warning is 1.2%, the highest false positive rate of urban road vehicle collision early warning is only 1%, and the pre-warning time of urban road vehicle collision is only 19.9s. It shows that this method has the characteristics of low miss rate, low false positive rate and low early warning time. It proves that the effect of urban road vehicle collision early warning is good, and can effectively improve the accuracy and efficiency of urban road vehicle collision early warning. However, this method does not consider the safety factors of urban road intersection environment. Therefore, in the next research, we need to analyze other safety factors to further ensure the impact early warning effect of urban road vehicles.

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An obstacle recognition method based on binary tree support vector machine for vehicle side blind area

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Abstract

Due to the problems of low recognition accuracy and long recognition time in the traditional vehicle side blind area obstacle recognition methods, a vehicle side blind area obstacle recognition method based on binary tree support vector machine is proposed. First, build the camera pinhole model, collect the vehicle side blind area image, after correcting the image distortion, preprocess the collected vehicle side blind area image through three steps of image denoising, graying and enhancement, then use Roberts operator to detect the edge of the processed image, screen the obstacle area in the vehicle side blind area, and finally use the binary tree support vector machine to filter the obstacle area according to the selected obstacle area, The obstacles in the lateral blind area of the vehicle are classified to identify the obstacles. The simulation results show that the proposed method has higher accuracy and shorter recognition time for vehicle side blind zone obstacle recognition.

Keyword - binary tree, support vector machines, lateral blind area, obstacle identification, roberts operator

1. Introduction

With the continuous development of economy, there are more and more vehicles, and the frequent occurrence of traffic accidents also causes the traffic accident rate to increase gradually [14]. Among them, because there is a blind area on the side of the vehicle, and the driver can not identify the obstacles in the blind area on the side during driving, and can not accurately judge the driving environment, which leads to traffic accidents from time to time, resulting in potential safety hazards. Therefore, in order to ensure driving safety, it is of great significance to identify obstacles in the lateral blind area of vehicles [8].

Zhang [17] proposed a method to identify obstacles in the blind zone in front of a ship based on depth learning. First, collect the images of obstacles in the blind zone in front of a ship, then use Sobel operator to divide the edges of the collected images of obstacles. According to the division results, identify obstacles in the blind zone in front of a ship through artificial neural network. Hu et al. [5] proposes a blind area obstacle recognition method based on inverse projection difference. The blind area obstacle image is obtained by taking pictures from adjacent angle cameras, and the obtained image is processed by inverse projection transformation and filtering. According to the processing results, the blind area obstacle is detected by inverse projection difference method to complete blind area obstacle recognition. However, the accuracy of the above two methods for obstacle recognition is low, resulting in poor recognition effect. Wang et al. [11] proposed a railway track obstacle recognition method based on YOLOv5 network model. The blind area image of railway track is obtained through sensors, and the acquired image is denoised. The YOLOv5 network is used to build a railway track obstacle recognition model. The preprocessed blind area image of railway track is input as a sample into the trained YOLOv5 network model, and the recognition results are output. Li [9] proposed a method to identify obstacles in the lateral blind area of vehicles based on the OpenCV function. The depth camera was used to obtain the environment image within the moving range of the intelligent car, and the OpenCV function was used to binarize and filter the obtained environment image. According to the processing results, the edge of the image was detected to identify obstacles in the lateral blind area of vehicles. However, the above two methods take a long time to recognize obstacles, resulting in low recognition efficiency.

Aiming at the problems existing in the above methods, a method for identifying obstacles in the lateral blind area of vehicles based on the binary tree support vector machine is proposed. The simulation experiments show that the method in this paper can quickly and accurately identify obstacles in the lateral blind area of vehicles, solve the problems existing in traditional methods, and lay a foundation for the auxiliary driving of vehicles.

2. Obstacle recognition method in vehicle side blind area

2.1. Vehicle side blind area image acquisition

In this paper, the camera pinhole model is built through the fish eye camera to collect the lateral blind area image of the vehicle [15]. Set the vehicle side blind area image to take $O_1(u_0, v_0)$ as the origin, the physical size of the vehicle side blind area image pixel on axis x as dx, the physical size on axis y as dy, and the horizontal and vertical coordinates as u_0, v_0, then convert the two coordinate systems:

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} 1/dx & 0 & u_0 \\ 0 & 1/dy & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{1}$$

Set the rotation matrix as R and the translation vector as t. Since the camera can be placed arbitrarily in space, a world coordinate system can be defined to describe the position of the camera coordinate system. Then:

$$\begin{bmatrix} \mathrm{X} \\ \mathrm{Y} \\ \mathrm{Z} \\ 1 \end{bmatrix} = \begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mathrm{X_w} \\ \mathrm{Y_w} \\ \mathrm{Z_w} \\ 1 \end{bmatrix} = \mathrm{M} \begin{bmatrix} \mathrm{X_w} \\ \mathrm{Y_w} \\ \mathrm{Z_w} \\ 1 \end{bmatrix} \tag{2}$$

Set the homogeneous coordinate of the vehicle side blind area image as $\mathrm{P'}$, the camera internal parameter matrix as A, the external parameter matrix as M, and the projection matrix as H, then obtain the vehicle side blind area image according to the coordinate position of the above formula:

$$\mathrm{SP'} = \mathrm{AMP'} = \mathrm{HP'} \tag{3}$$

Since there is distortion in the image shooting process, the radial and tangential distortion parameters in the image are corrected [10]. Then the radial distortion correction can be expressed as:

$$\begin{cases} x' = x(1 + k_1 r^2 + k_2 r^4 + k_3 r^6) \\ y' = y(1 + k_1 r^2 + k_2 r^4 + k_3 r^6) \end{cases} \tag{4}$$

Tangential distortion correction can be expressed as:

$$\begin{cases} x' = x + (2p_1 y + p_2(r^2 + 2x^2)) \\ y' = y + (p_1(r^2 + 2y^2) + 2p_2 x) \end{cases} \tag{5}$$

where x, y represents the distortion point, x', y' represents the point coordinate after distortion correction, and r represents the distance from the distortion point to the image center.

2.2. Vehicle side blind area image preprocessing

Since the collected vehicle side blind area image is easily affected by the surrounding noise and environment, which results in the low discrimination between the target object to be identified in the image and the surrounding environment. In order to reduce the workload of subsequent target recognition, the following steps are used to preprocess the collected vehicle side blind area image.

(1) Image denoising

During the process of image acquisition, it is easy to be affected by the external environmental noise, which leads to the reduction of image quality and the concealment of details, which adds difficulties to the further processing and analysis of the vehicle side blind area image. Therefore, it is necessary to denoise the collected blind area image [7]. In addition, in the process of vehicle lateral blind area image denoising, it is also necessary to preserve the details of the original image as completely as possible to avoid increasing the subsequent workload [12].

Median filtering is a typical nonlinear filtering algorithm. Its basic principle is to calculate the median of the gray value of the neighboring points around the pixel points, and replace the gray value of the original pixel points with this value. In this paper, the median filtering method is used to denoise the vehicle side blind area image. Set the original vehicle side blind area image collected as $f(i, j)$, and obtain a smooth image $g(i, j)$:

$$g(i, j) = \frac{1}{M} \sum_{i,j \in S} f(i, j) \tag{6}$$

(2) Image graying processing

The vehicle side blind area image also contains many levels of color depth information. Like the image displayed in the old black-and-white TV, the black-and-white degree between points is different, and this is the depth. The color depth information of pixel points in gray image is called gray value, which is usually obtained by measuring the brightness of each pixel in a single visible light, and is generally divided into 256 levels [18].

In this paper, the weighted average method is used to grayize the color vehicle side blind area image, which can be used for image classification and recognition later. Color image pixels are composed of R, G and B components, while gray image pixels have only one gray scale. The vehicle side blind area image after graying processing is fast, and the amount of information contained is enough for the following morphological analysis.

By decomposing the color of the pixels in the vehicle side blind area image into three components, R, G and B, and then calculating the gray value of each pixel respectively, and then reassigning all the pixels in the vehicle side blind area image, the vehicle side blind area image is converted into a gray image [6]. The expression is:

$$F(x, y) = 0.299 * R(x, y) + 0.587 * G(x, y) + 0.114 * B(x, y) \tag{7}$$

(3) Image enhancement processing

Image enhancement technology mainly emphasizes the features of some regions of interest in the image and suppresses the features of regions of no interest in order to obtain more effective information and enhance the effect of image recognition. In this paper, the image enhancement technology based on gamma transform is used to correct the part with low or high gray value in the vehicle side blind area image, improve the contrast of the image, and thus enhance the details of the vehicle side blind area image [16]. The formula of gamma transformation is as follows:

$$S_{out} = cr_{in}^{\gamma} \tag{8}$$

where r_{in} is the pixel value of the vehicle side blind area image, which is a non negative real number. c is a constant, called the gray scale coefficient, which is used to lift the gray scale value of the vehicle's lateral blind area image as a whole. The value range is [0,1], usually 1.

In the gamma curve, γ value takes 1 as the dividing line. When $\gamma < 1$, with the decrease of γ value, the expansion effect of gamma transform on the low gray level part of the vehicle lateral blind area image is gradually enhanced, specifically, the brightness of the overall vehicle lateral blind area image is reduced, At $\gamma > 1$, with the increase of γ value, the expansion effect of gamma transform on the high gray part of the image is gradually enhanced, specifically to improve the brightness of the overall vehicle side blind area image [4]. Therefore, by changing the γ value, we can expand the details of low gray or high gray parts in the vehicle side blind area image.

2.3. Obstacle screening in vehicle side blind area

By detecting the edge information of the vehicle side blind area image, the target contour information, including the size and position of the target, can be obtained, so that the uninterested part in the image can be deleted, and the interested part, that is, the obstacle area, can be obtained. Edge detection of vehicle side blind area image is the most important link in obstacle recognition, and Roberts operator is a simple gradient operator with simple operation. Therefore, this paper uses Roberts operator to detect the edge of vehicle side blind area image, and screen the obstacles in vehicle side blind area according to the detection results.

Set the grayscale image after image enhancement as $Q(i,j)$ and the edge image as $R(i,j)$. Obtain the edge of the vehicle side blind area image in two directions, including the diagonal direction, horizontal direction and vertical direction, where the diagonal direction is:

$$R(i,j) = |Q(i,j) - Q(i+1,j+1)| + |Q(i,j+1) - Q(i+1,j)| \tag{9}$$

The horizontal and vertical directions are:

$$R(i,j) = |Q(i+1,j) - Q(i,j)| + |Q(i,j+1) - Q(i,j)| \tag{10}$$

According to the above image edge detection results, the obstacles in the lateral blind area of the vehicle are screened, and the specific steps are as follows:

(1) Set the area of interest in the lateral blind area of the vehicle as ROI, fit and compare the image detection window with the above edge detection results to obtain the area of interest. The fitting and comparison results are as follows:

$$S(i,j) = R(i,j) * ROI \tag{11}$$

(2) Judge whether the edge of the vehicle side blind area image is closed. If it is closed, fill the closed connected area, that is, the obvious object contour in the vehicle side blind area image [19].

(3) In the formula, the number of pixels occupied by the connected area is D_{Area}, the height of the surrounding rectangle is D_{Hight}, the width is D_{Width}, and the shape characteristic coefficient of the suspected obstacle is $S, D, D_{low}, D_{high}, D_{Ratio}$. According to the filled connected area, the area, size and other parameters are filtered:

$$\begin{cases} D_{Area} \geq S \\ D_{Hight} \geq D \cap D_{Width} \geq D_{low} \cap D_{Width} \leq D_{high} \\ \frac{D_{Area}}{D_{Hight}*D_{Width}} \geq D_{Ratio} \end{cases} \tag{12}$$

When the above formula is met at the same time, the connected area obtained is the suspected lateral blind area obstacle area of the vehicle.

2.4. Obstacle recognition based on binary tree support vector machine

Binary Tree Support Vector Machine (BT-SVM) is a multi class classification algorithm based on the structure of an ambiguous tree to improve SVM. The basic idea of the algorithm is: first, divide all categories into two subcategories from the root node, and then divide each subcategory into two subcategories. Each subcategory is divided into two subcategories at the next level, Finally, stop iteration when the nodes obtained contain only one category, and then a binary classification tree is obtained, which completes the process of transforming the original multi category classification problem into a two category classification problem for a series of category sets . MTSVM can be divided into complete binary tree support vector machine and partial binary tree support vector machine according to the different partition rules selected during each binary classification of nodes.

The complete binary tree is that every time a node containing multiple categories is divided, its contained categories are equally divided into two categories, and two subclass nodes containing the same number of categories are obtained, Partial binary tree means that each time a node with multiple categories is divided, only one category is separated from all categories [2].

The binary tree support vector machine algorithm steps are as follows:

The first step is to initialize the class set $C = (1,2,\ldots,k)$ and the training sample set is S.

The second step is to generate a binary tree structure by constructing a binary tree generating function.

Third, in the binary tree structure generated in the second step, each non leaf node contains two category subsets, called A_1,A_2. All the samples in the class set A_1 of the training set S constitute a training subset labeled+1, and all the samples in the class set A_2 of the training set S constitute a training subset labeled - 1. This constitutes a binary classification problem, through which the SVM classifier can be produced. Then, each non leaf node on the binary tree is trained to obtain a class II SVM classifier belonging to each node [13, 3, 1].

Step 4: Test. This step classifies the samples of unknown categories, starting from the classifier of the root node, and according to the results of the current classifier, the samples go down one level at a time until they reach a leaf node. At this time, the category set of the leaf node is the category information of the sample.

Based on the above, this paper uses the binary tree support vector machine to classify the obstacles in the lateral blind area of the vehicle according to the selected obstacle area and identify the obstacles, which is divided into two steps:

The first step is the training process. For the classification problem with k categories, $k-1$

TWSM classifiers are obtained through training. Construct the first TWSM classifier: classify the training samples belonging to the first category into category+1, and classify the training samples belonging to category $2,3,\ldots,k$ into category - 1 to obtain the classifier TWSM, Construct the i-th TSVM classifier: classify the training samples belonging to the i-th category into+1 category, and classify the training samples belonging to the $1,2,3,\ldots,$k-th category into - 1 category to train the classifier TSVMI, Finally, the $k-1$ th TSVM classifier is constructed: the training samples belonging to the $k-1$ class are classified as+1 class, and the training samples belonging to the k class are classified as - 1 class. The classifier $TSWM(k-1)$ is obtained through training. If the number of samples of the+1 class and the - 1 class is large in the training process of a TSVM classifier, different penalty coefficients can be imposed on the sample class. The steps of the above training process are as follows:

(a) Let $i=1$, if $i \leq k-1$, construct the following two quadratic programming problems:

$$\min \frac{1}{2} \|K(A_i, A') + e_i\| + c_i \epsilon \geq e_i \tag{13}$$

$$\min \frac{1}{2} \|K(A_i, A') + e_i\| + c'_i \epsilon' \geq e'_i \tag{14}$$

where c_i, c'_i represents the penalty coefficients of+1 and - 1 respectively, ϵ, ϵ' represents the interval relaxation variable, A_i represents all training samples of the i class, A' represents all training samples of the $i+1, i+2,3,\ldots,k$ class, e_i, e'_i represents the unit vector of the corresponding dimension, and K represents the internal product kernel function.

(b) Solve the two programming problems in step (b), get (w_i, b_i),(w'_i, b'_i) and, and determine two hyperplanes of D, where H_i is the hyperplane of class i, T_i is the general hyperplane of class $i+1, i+2,3,\ldots,k$, and T_{k-1} is the hyperplane of class k.

(c) $i=i+1$, return to step (b).

The second step is the test process. By traversing the partial binary tree structure obtained in the first step, the new input sample x_0 to be classified is classified. The test process steps are as follows:

(a) Order $i=1$,

(b) If $i \leq k-1$, proceed to the next step, Otherwise, x_0 belongs to Class k, and ends and exits,

(c) Calculate the distance from x_0 to hyperplane H_i and T_i,

(d) If the distance from x_0 to hyperplane H_i is less than the distance from A to hyperplane T_i, then x_0 belongs to category i, and the test ends and exits. Otherwise, $i=i+1$, and return to step (b).

According to the above classification results, the expression for the identification of obstacles in the lateral blind area of vehicles is:

$$W_s = \frac{e_i S(i,j)}{H_i K(A_i, A\prime)} \tag{15}$$

3. Simulation experiment analysis

In order to verify the effectiveness of the obstacle recognition method based on binary tree support vector machine proposed in this paper in practical application, M1 passenger cars are selected as the target vehicles for a simulation experiment analysis. Taking the recognition accuracy and recognition time of the obstacles in the lateral blind area of the vehicle as the experimental indicators, the recognition method based on depth learning proposed in Zhang [17] and the recognition method based on inverse projection difference proposed in Hu et al. [5] are used as the comparison method to conduct a simulation analysis with the method in this paper.

The test environment parameter settings are shown in Table 1.

Tab. 1 - Test environment parameter settings

Weather condition	Good climatic conditions
air temperature	12~25℃
wind speed	10 m/s
Light intensity	Natural lighting conditions
Road horizontal flatness	Less than 1%
Road length	500 m

Fig. 1 - Overall view of test scenario construction

The panorama of the test scenario is shown in Figure 1.

The identification method of obstacles in the lateral blind area of vehicles proposed in this paper based on the binary tree support vector machine, the identification method based on depth learning proposed in Zhang [17] and the identification method based on inverse projection difference proposed in Hu et al. [5] are used to compare and analyze the identification accuracy of obstacles in the lateral blind area of vehicles. The comparison results are shown in Figure 2.

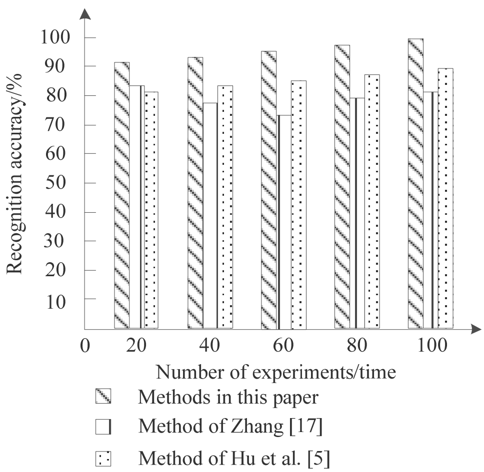

Fig. 2 - Comparison results of obstacle recognition accuracy of three methods in vehicle side blind area

Tab. 2 - Comparison results of obstacle recognition time of three methods in vehicle side blind area/s

Number of experiments/time	Methods in this paper	Method of Zhang [17]	Method of Hu et al. [5]
10	12.21	18.62	25.62
20	21.85	18.96	26.42
30	13.15	19.25	26.95
40	13.65	19.88	27.42
50	13.86	20.21	27.85
60	14.05	21.32	28.12
70	14.68	21.68	28.65
80	15.42	22.36	29.15
90	15.93	23.42	29.62
100	16.42	24.65	30.62

It can be seen from Figure 2 that the accuracy of the vehicle side blind area obstacle recognition method proposed in this paper based on the binary tree support vector machine for vehicle side blind area obstacle recognition can reach up to 100%, the accuracy of Zhang [17] for vehicle side blind area obstacle recognition can reach up to 84%, and it can reach up to 88% for Hu et al. [5], This paper proposes a method based on binary tree support vector machine to identify obstacles in the lateral blind area of vehicles, which has the highest accuracy and the best recognition effect.

In order to further verify the effectiveness of the method in this paper, the identification method of obstacles in the lateral blind area of vehicles based on the binary tree support vector machine proposed in this paper, the method of Zhang [17] and Hu et al. [5] are used to compare and analyze the time spent in the identification of obstacles in the lateral blind area of vehicles. The comparison results are shown in Table 2.

According to the data in Table 2, it can be seen that the time used for the identification of obstacles in the lateral blind area of vehicles by the method proposed in this paper based on the binary tree support vector machine is within 16.42s, the time used for the identification of obstacles in the lateral blind area of vehicles by Zhang [17] is within 24.65s, and the time used for the identification of obstacles in the lateral blind area of vehicles by Hu et al. [5] is within 24.65s, This paper proposes a method based on binary tree support vector machine to identify obstacles in the lateral blind area of vehicles, which takes the shortest time and has the highest recognition efficiency.

4. Conclusion

Due to the poor effect and low recognition efficiency of traditional methods for vehicle side blind area obstacle recognition, this paper studies the method of vehicle side blind area obstacle recognition based on binary tree support vector machine. By building a camera pinhole model, the vehicle side blind area image is obtained, and the median filtering method, weighted average method and gamma transform method are used to denoise, grayscale and enhance the obtained vehicle side blind area image. According to the image preprocessing results, Roberts operator is