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# Research on Lane Detection Method with Shadow Interference

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**Abstract:** Lane detection is one of the key technologies in the field of intelligent transportation. It is widely used in assisted driving systems, lane departure warning systems and vehicle anti-collision systems, which is of great significance for improving traffic safety. Due to the complexity and variety of road scenes, this paper studies the lane detection with shadow interference. We present an efficient and robust algorithm for detecting lanes based on the vertical direction IPM sub-picture reconstruction and its hierarchical image fusion. Firstly, the road IPM top view is obtained, and then decomposed and reconstructed by wavelet. In addition, the Canny edge detection algorithm is employed to extract edge information of the reconstructed maps. Finally, we use the improved Hough transform to detect lane lines. We present an efficient and robust algorithm for detecting lanes with shadow interference. This method greatly reduces the interference of shadows on images through wavelet decomposition and reconstruction, which can detect the lane line more accurately. The experimental results show that the algorithm can accurately detect the lane line with shadow interference and has certain robustness.

**Key Words:** Lane detection, Image processing, Edge detection, Hough transform

## 1 Introduction

In recent years, in order to solve various traffic problems mainly caused by traffic accidents and traffic congestion, countries all over the world have carried out various researches in the field of intelligent transportation systems. Lane detection is the basis for realizing the intelligent driving technology of smart cars, and it is also one of the core researches of driverless technology. Therefore, the study of lane detection is of paramount importance. Lane detection based on Machine vision provides the smart car with the most basic road information for automated driving. The edge of lane[1], geometry of the road[2], and texture information of the lane are significant features in lane detection[3]. Separating the lane line from the road background makes it possible to clearly identify the lane and to acquire information such as the position of the vehicle relative to the lane. According to the principle difference of the detection algorithm, the lane detection algorithm of the structured road can be divided into the feature-based method and the model-based method.

The feature-based method mainly uses image features of the road, such as edge, color, texture direction, etc., and then uses threshold segmentation, region growing or image classification techniques to extract lane lines. The method detects the lane lines based on the difference between the lane and other backgrounds on the image features to detect, regardless of the geometrical information of the road. So, the calculation is relatively simple. Lane lines have prominent edge features as distinct road signs, so the use of edge enhancement operators for detection is the most common method. Yoo[4] uses the gradient information of the lane edge as the feature information of the lane detection, and dynamically updates the edge information of the lane by dynamically updating the conversion vector of the RGB image to the gray image and combining the adaptive Canny edge detection. This method enhances the lane line, effectively reducing the impact of noise edges, but the adaptability to some harsh environments is poor.

The model-based approach uses road prior knowledge and specific curve parameters to describe lane lines, simplifying lane detection to the process of calculating model parameters. Common road models include straight lines, parabolas, linear hyperbolas, and splines. Li[5] divides the region of interest into two sub-regions, and then uses the Hough transform to extract the line segments in each sub-region to fit the lane lines. This method can achieve the fitting of straight or curved, solid or dashed lane lines, but because the region of interest is only divided into two sub-regions, the fitting effect is not ideal for lane lines with large curvature.

Lane detection algorithm should adapt to complex and varied road environments, such as shadows, lights, fog and rain. Lane detection becomes challenging when roads contain shadowed areas and non-shadowed areas. Shadow of trees, buildings or other vehicles on the surface of the road can lead to false edges. If the edge feature extraction is performed directly on the original image, a large number of non-target edges outside the lane target are also extracted together. To eliminate this shadow effects, [6] transformed the color space to Hue Saturation Lightness (HSL), Lab color space and others that were illumination invariant. Another idea to reduce the effect of casting shadows is to filter edges that are not vertical direction like[7] and authors in [8] use controllable filters to detect specific angles in the direction of the lane.

The rest of this paper is as follows. Section 2 introduces image preprocessing methods, section 3 presents the lane detection method with shadow interference, section 4 introduces the experimental results and related analysis, and section 5 summarizes the paper.

## 2 Image Preprocessing

In order to remove noise and reduce useless information and improve the algorithm efficiency, image preprocessing plays a very important role. The pre-processed image can preserve the useful features in the image to the maximum extent and ensure the validity of the algorithm. Image preprocessing can also facilitate subsequent detection.

### 2.1 Inverse Perspective Mapping (IPM)

The inverse perspective mapping is to generate a top view of the road image. If edge extraction is performed directly on the original image (front view), a large number of non-target edges outside the lane line target will also be extracted together, such as trees, sky, traffic signs, vehicles, pedestrians, etc., which constitute interference source of lane detection. There is almost no such problem in the edge extraction of selected road areas on the IPM map (top view) and the number of interference points is small. A rectangular area (192*130 pixels in two-lane mode and 560*130 pixels in four-lane mode) is initially selected on the original image (640*480 pixels), which is the ROI of the process of vehicle driving.

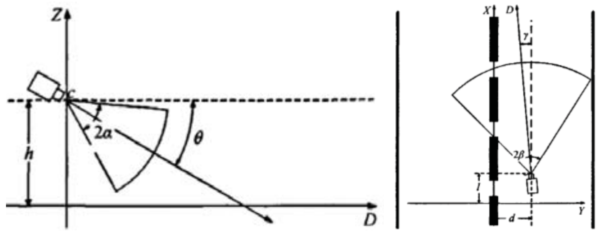
(a) two-lane mode (b) four-lane mode
Fig. 1: ROI of Lane (Source: Caltech Lanes Dataset [9])

It can be seen from Fig. 1 that the perspective mapping process of the three-dimensional road scene on the two-dimensional image plane brings disadvantages to the subsequent edge extraction and lane line model. Inverse Perspective Mapping (IPM) is the inverse process of perspective mapping. It can use the camera's angle, height and other position information to establish a three-dimensional coordinate system, catching a top view of the scene. After the inverse perspective mapping, the lane lines that originally had the intersecting trend are converted into parallel lines in the top view, which is more convenient for detection. The typical IPM formula in the field of inverse perspective mapping technology was derived by M. Bertozzi et al. and successfully applied to the GOLD autonomous vehicle. The relationship between the road coordinates (x, y, 0) and the image coordinates (u, v) in the world coordinate system:

$$u(x,y,0)=\frac{cot\left\{\frac{h\times sin\left[cot\left(\frac{y-d}{x-l}\right)\right]}{y-d}\right\}-(\theta-\alpha)}{2\alpha/(m-1)} \tag{1}$$

$$v(x,y,0)=\frac{cot\left(\frac{y-d}{x-l}\right)-(\gamma-\beta)}{2\beta/(n-1)} \tag{2}$$

Formula (1) (2) Derivation engineering background is shown in Fig. 2, where the camera's position coordinates in the world coordinate system are (l, d, h) meters, the camera resolution is m × n pixels, and the field of view is 2α × 2β radians, the yaw angle is γ radians, and the pitch angle is θ radians.




(a) side view (b) top view
Fig. 2: Camera position parameter

The relationship between the point Q (x, y, z) of the coordinate system of the world and its image point q (u, v) is as follows:

$$Z\begin{bmatrix}u\\v\\1\end{bmatrix}=\begin{bmatrix}\frac{1}{d_x}&0&u_0\\0&\frac{1}{d_y}&v_0\\0&0&1\end{bmatrix}\begin{bmatrix}f&0&0&0\\0&f&0&0\\0&0&1&0\end{bmatrix}\begin{bmatrix}R&t\\0^T&1\end{bmatrix}\begin{bmatrix}x\\y\\z\\1\end{bmatrix}$$
$$=\begin{bmatrix}a_x&0&u_0&0\\0&a_y&v_0&0\\0&0&1&0\end{bmatrix}\begin{bmatrix}R&t\\0^T&1\end{bmatrix}\begin{bmatrix}x\\y\\z\\1\end{bmatrix}=M_tM_0\begin{bmatrix}x\\y\\z\\1\end{bmatrix}=M\begin{bmatrix}x\\y\\z\\1\end{bmatrix} \tag{3}$$

In formula (3):

Z: Normalized coefficient;

$u_0, v_0$: Pixel coordinates of the center point in the image;

$d_x$, $d_y$: Size of the sensor in horizontal and vertical directions;

$f$: Focal length, $a_x = f/d_x$, $a_y = f/d_y$, $0^T = (0,0,0)$;

Vector t: Relative positional relationship between the camera coordinate system and the origin of the world coordinate system;

Matrix R: The attitude relationship between the camera coordinate system and the coordinate system of the world coordinate system, called the camera rotation matrix;

$M_t$: Camera inner parameter matrix, $M_0$: Camera external parameter matrix, M: Projection matrix;

After obtaining the projection matrix M by camera calibration, camera focus, optical center, camera height, camera yaw angle and pitch angle, perform IPM conversion as follows:

(1) Only select the road region of interest in front of the vehicle for reverse transmission transformation, and only preprocess the partial IPM top view.
(2) Calculate the image coordinates in the corresponding image coordinate system using the formula (3) for each point coordinate in the world coordinate system.
(3) The IPM transformed image is assigned a gray value pixel by pixels according to the image coordinate value.

After implementing the above three steps, the road top view can be obtained as shown in the Fig. 3. Comparing the original and the top view, it is obvious that the lane lines in the top view are clearer (substantially parallel), and the road is clear and the hand can divide the useful road area, so it is easier to detect.

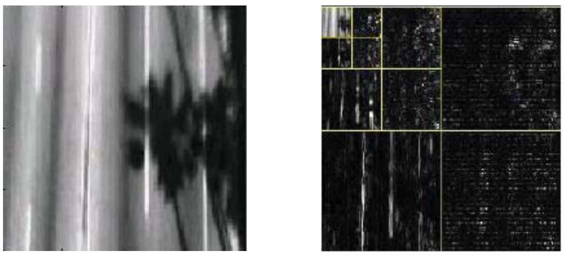
(a) ROI of the original image (b) IPM top view

Fig. 3: ROI of the non-shadowed area IPM top view

Fig. 4: ROI of the shadowed area IPM top view

### 2.2 Wavelet Decomposition and Reconstruction

Before performing wavelet decomposition, the IPM map obtained is first preprocessed to cut out useless information. For lane IPM images, the vertical edges should be enhanced, and the horizontal and oblique angles should be weakened. The flexibility of wavelet image processing just happens to meet this need. After the image is decomposed by wavelet, you can choose to reconstruct the sub-picture vertically. This paper uses the sym wavelet system to complete image processing.



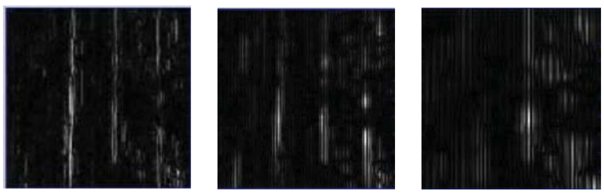
(a) IPM map (b) wavelet decomposition map

Fig. 5: three layers sym3 wavelet decomposition map

It is easy to see from the subgraph after decomposition that the lane line is most obvious in the vertical subgraph, while the lane line in other directions is very weak and almost invisible.

(a) First layer (b) Second layer (c) Third layer

Fig. 6: Vertical decomposition of each layer



(a) First layer (b) Second layer (c) Third layer

Fig. 7: Vertical reconstruction of each layer

It has been found that the reconstruction of the original image with the first and second layers can reflect the position of the lane line well, and the shadow interference is removed very cleanly. Especially the original image reconstructed from the second layer of the vertical detail sub-picture, the visual effect of the lane line is very good.

### 2.3 Image Enhancement

The purpose of image enhancement is to highlight certain information in the image while attenuating or removing some useless information. Specific image enhancement techniques include image contrast enhancement, brightness enhancement, contour enhancement, and so on. For the lane IPM image, the edge information in the vertical direction needs to be enhanced, and the information of the horizontal and other unrelated directions needs to be weakened. Different images have different processing requirements for enhancement, and appropriate enhancement methods should be adopted according to the characteristics of image applications. After the image enhancement process, the lane line extraction will be more complete.

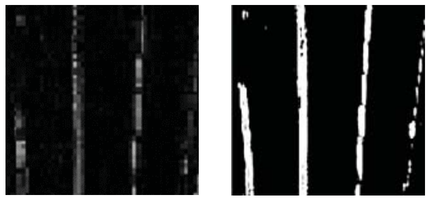


Fig. 8: Lane map and enhanced lane map

## 3 Lane Detection with Shadow Interference

This paper uses the model-based lane line detection algorithm. To extract the lane line information, the edge detection must be done firstly.

### 3.1 Edge Detection

The purpose of edge detection is to segment the object and the background so as to highlight the edge information of the lane line and prepare for the accurate identification of the lane line. In addition, roads are susceptible to interference such as light, which can affect detection algorithms, and edge detection can overcome this. This paper mainly studies the Sobel operator and Canny operator in the edge detection operator.

#### 3.1.1 Sobel Edge Detection

Sobel operator is a discrete first-order difference operator commonly used for horizontal and vertical edges. The Sobel operator weights the position of the image pixel field and has the largest neighboring weight. The operator consists of two sets of 3x3 matrixes, which are horizontal and vertical, respectively, and are convolved with the image to obtain luminance difference approximations. If $A$ represents the original image, $S_x$ and $S_y$ represent images detected by the lateral and longitudinal edges, respectively, and the formula is as follows:

$$S_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} A \quad S_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} A \qquad (4)$$

The horizontal and vertical gradient approximations for each pixel of the image can be combined using the following formula to calculate the magnitude of the gradient.

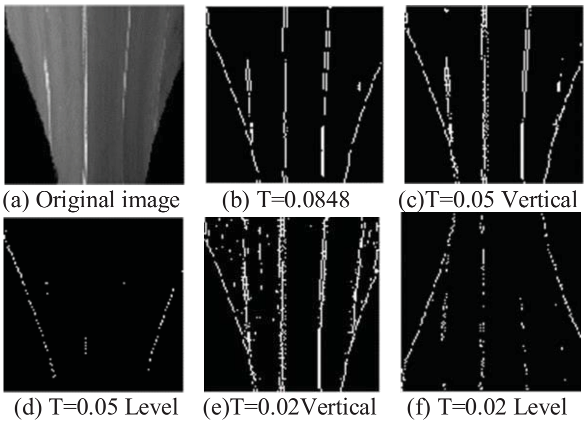
$$G = \sqrt{S_x{}^2 + S_y{}^2} \quad (5)$$

The gradient direction can be calculated using the following formula.

$$\theta = \arctan(S_y/S_x) \quad (6)$$

If the above angle θ is equal to zero, it means that the image has a vertical edge.

In order to compare the detection results, the Sobel operator with adaptive threshold is used to extract the edge features of the same image. The result is shown in Fig. 9.



(a) Original image (b) T=0.0848 (c)T=0.05 Vertical
(d) T=0.05 Level (e)T=0.02Vertical (f) T=0.02 Level

Fig. 9: Sobel edge detection results of the road IPM map

The edge detection result of Sobel operator shows that when the threshold value is 0.02, all lane lines can be detected in the vertical direction, but at the same time, more interference points are detected. All lane lines cannot be detected under the adaptive threshold, and there are some miss detections. The detection speed of the Sobel operator is indeed very fast. However, for the actual track image sequence, it is difficult to determine the adaptive Sobel operator threshold without missed detection, so the Sobel operator method has limitations.

### 3.1.2 Canny Edge Detection

John Canny proposed the Canny algorithm in 1986. The Canny algorithm is a multi-level edge detection algorithm, which belongs to the method of first obtaining the derivative after smoothing. The specific process of the Canny operator is as follows:

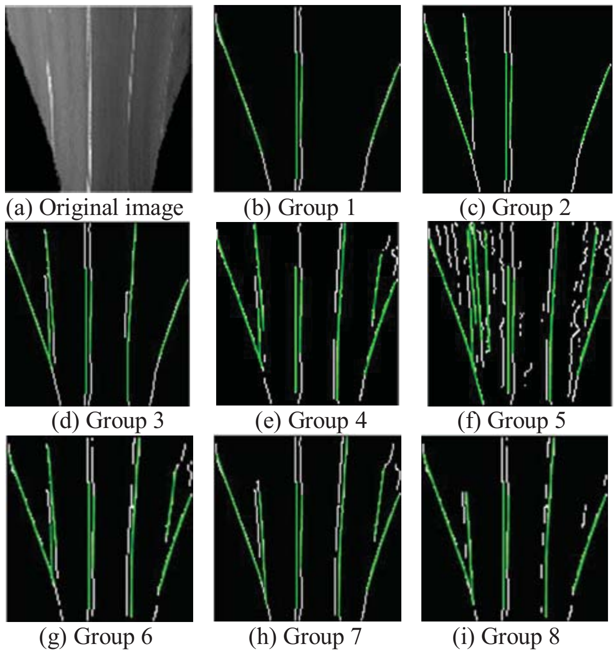
(1) Smooth the image by using a Gaussian filter.

(2) Calculate the gradient amplitude and direction by using the first-order partial derivative finite difference.

(3) Performing non-maximal suppression on the gradient amplitude;

(4) Detection and connection of edges using a double threshold algorithm

The Canny edge detection algorithm uses a double threshold to obtain an edge image with few false edges based on the high threshold. But the threshold is high, so the detected edge may not be closed. Therefore, another low threshold is set. Use the Canny operator in the OpenCV library function cvCanny to perform edge detection on the IPM road map, and then use the Hough transform to detect the lane line. Eight groups of threshold combinations were used for detection.



(a) Original image (b) Group 1 (c) Group 2
(d) Group 3 (e) Group 4 (f) Group 5
(g) Group 6 (h) Group 7 (i) Group 8

Fig. 10: Canny edge detection results of the road IPM map

The value of threshold1 or threshold2 and the effect of detection by cv Canny are as follows.

Group1: threshold1=30, threshold2=500, three missed detections. Group2: threshold1=30, threshold2=400, two missed detections. Group3: threshold1=30, threshold2=300, one missed detection. Group4: threshold1=30, threshold2 =150, no missed detections, a few broken edges. Group5: threshold1=30, threshold2=50, no missed detections, many broken edges. Group6: threshold1=50, threshold2=150, no missed detections, less broken edges, good effect. Group7: threshold1=75, threshold2=150, no missed detections, less broken edges, good effect. Group8: threshold1=100, threshold2=150, one missed detection.

The experimental results show that:

(1) For this image, when the threshold2=150 and the threshold2/threshold1 is between 2 and 3, the effect of detection is optimal.

(2) The larger the threshold1, the fewer the fine edges, and vice versa. The larger the threshold2, the smaller the total amount of edges, and vice versa.

(3) The more the number of edges, the larger the amount of computation of the Hough transform, and the excessive amount will lead to false check. The smaller the number of edges, the smaller the amount of computation of the Hough transform, too small will lead to missed detections.

In short, too much or too little edge detection is not conducive to the Hough transform to detect the lane line. Only on the appropriate edge detection result map, the Hough transform can effectively detect the lane line. Therefore, the edge detection and pre-processing results have a direct effect on the Hough transform.

## 3.2 Improved Hough transform

In order to facilitate the analysis of the actual road, the appropriate constraint assumptions are usually used to simplify the model. The following assumption is made in this paper: The geometric model of the road is only presented as a straight line. This section will explore the optimal lane line recognition algorithm with shadow interference based on the constraint assumption.

Hough transform is a classical method for detecting parametric shapes in image processing and pattern recognition, and is also a key technical link for implementing lane detection. The method utilizes the duality of point-to-line and searches for a particular shape by voting to record the local maximum of the cumulative result in the parameter space. Line recognition based on Hough transform is a description of transforming a straight line in image space into a parameter space. Perform statistical calculations on all points that may fall on the boundary of the line. Based on the results of the statistics, it can determine the extent to which the point belongs to the line. As shown in Fig. 11, any point (x, y) in the image that belongs to the line is mapped to a sinusoid within the parameter space $(\theta,\rho)$. All points on the line will pass through the same $(\theta,\rho)$ point.

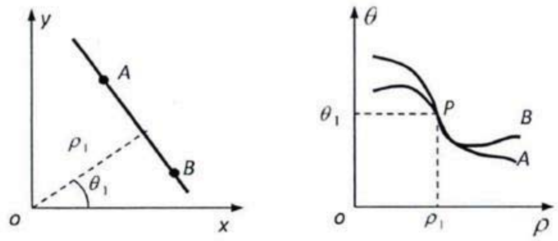



Fig. 11: Principle of Hough Transform

By detecting the $(\theta,\rho)$ point of the cumulative distribution, catching the point $(\theta,\rho)$ which have the largest value, and further solving the parametric equation. The parameter description of the straight line is obtained. The parametric equation is as follow.

$$\rho = x\cos\theta + y\sin\theta \tag{7}$$

The specific implementation steps are as follows:

Step 1: Create a $\rho-\theta$ parameter space and initialize an empty two-dimensional accumulation array, which is essentially a counter, and then create a linked list for storing the position of the plane spatial point of the image. At this time, set the value range of $\rho$ and $\theta$. And calculate the number of points that fall into the polar coordinate space.

Step 2: Hough transform the image, and traverse each point $\theta$ after quantization, calculate the corresponding $\rho$ according to $\rho = x\cos\theta + y\sin\theta$, add 1 to the corresponding accumulated array, and get Hough Transform matrix when all points are converted. At the same time the counter counts statistically.

Step 3: Find the maximum value of the $\rho-\theta$ parameter space by setting the threshold value to obtain the geometric quantity of the line, thus detecting the straight line. Continue to detect, clear the counter and repeat the above steps.

The range of $\theta$ is $[-90°, 90°]$ and the range of $\rho$ is [-D, D]. D represents the distance between the diagonals. The standard Hough transform has high fitting precision and strong adaptability. However, when detecting a straight line, the Hough transform needs to traverse all the $\theta$ values for one feature point, and then find the value corresponding to $\rho$. In the case of a lot of feature points, the amount of calculation is very large. In this paper, the wavelet image is used to preprocess the lane image, and the role of the polar coordinate parameter $\rho$ in the Hough transform is reduced. Then the Hough transform is used to detect the lane. For an image with a pixel of M*N, the range of $\rho$ is usually $\left[-\sqrt{2}M/2, \sqrt{2}N/2\right]$. Furthermore, through experimental observation, we set the value range of $\theta$ is nearly$[-30°, 30°]$. In this case, the amount of calculation will be greatly reduced.

The algorithm of lane detection with shadow interference is introduced so far. The specific algorithm flow is firstly obtain the road IPM top view. Secondly, it wavelet-decompose the IPM road top view. Then it select the 1 and 2 layer vertical sub-pictures to reconstruct the IPM road map. Thirdly, perform image enhancement processing. The next step is to use the Canny edge detection method to detect the road edge map. Finally we can use the Hough transform of the polar angle constraint to detect the lane line. The result is shown in Fig. 12.

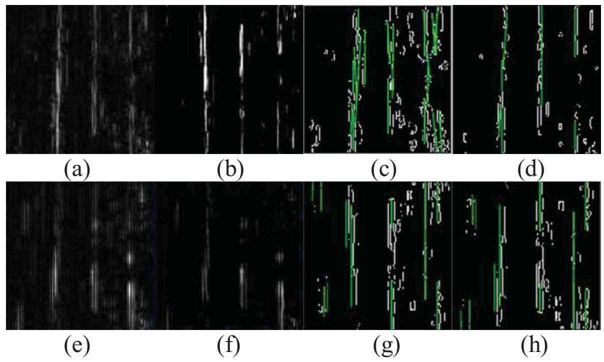



Fig. 12: The results of Lane detection

(a) First-level reconstructed IPM map. (b) First-level reconstructed IPM map after enhancing contrast. (c) Hough transform detection results of the First-level reconstructed IPM map. (d) Hough transform detection results of the First-level reconstructed IPM map after enhancing contrast. (e) Second-level reconstructed IPM map. (f) Second-level reconstructed IPM map after enhancing contrast. (g) Hough transform detection results of the Second-level reconstructed IPM map. (h) Hough transform detection results of the Second-level reconstructed IPM map after enhancing contrast. The summary of the experimental results shows that the Hough transform can accurately find the lane on the processed IPM map, but individual lane lines will be missed. There are two ways to solve the missed detection. The first one is to enhance the image before the Hough transform, but the effect of this method is limited. The second is to fuse the detection results of the first-level and second-level reconstruction maps to improve the robust of detection. Because it is found from the experimental results, the position of the missed lane line on the first-level and second-level reconstruction maps is uncertain and complementary.

## 4 Experimental Results

The experimental hardware conditions of this paper are a PC with Intel(R) Core(TM) i7-6700 CPU @3.40GHz, AMD Radeon R7 200 Series, and 8G memory. The software condition is 64-bit Windows10 system. The development integration environment is Visual Studio 2015. The development language is C++, configured with Opencv3.2 toolkit.

In order to evaluate the effectiveness of the proposed algorithm in this paper, the experimental data is selected from the Caltech Lanes Dataset [9]. The dataset is a road image of the road ahead of the vehicle obtained by the in-vehicle camera. It contains a total of four 640*480 pixels road videos in the urban scene, and two videos with shadow interference are selected, totaling 568 labeled frames containing 2205 marked lanes. In order to facilitate the observation of the detection effect, the detected lane lines are marked with green respectively.

Fig. 13: The results of lane detection method in this paper

Since the lane lines in the actual road scene generally have a certain width, the detection result of the algorithm is marked by a single line. In this paper, it is considered that as long as the position indicated by the detection result falls within the width range of the lane line, it is not considered as a detection error. For the presence of a lane line in the test image, but the algorithm does not detect it, it is considered that a missed detection has occurred. For all test images in the dataset, this paper evaluates the three indicators of false detection rate, missing detection rate and correct detection rate. We can evaluate the effect of the algorithm on the frames and lanes for the two object units. When the unit is a frame, all the lanes in the frame image must be correctly detected to calculate the frame image detection.

Table 1: Evaluation in units of frame images

| Clip | Name | Frames | Detected frames | Correct rate |
|---|---|---|---|---|
| 1 | Washington1 | 336 | 320 | 0.952 |
| 2 | Washington2 | 232 | 222 | 0.957 |
| total | | 568 | 542 | 0.954 |

Table 2: Evaluation in units of lanes

| Clip | lanes | Detected lanes | False lanes | Missing lanes | False rate | Missing rate |
|---|---|---|---|---|---|---|
| 1 | 1274 | 1302 | 34 | 6 | 0.027 | 0.005 |
| 2 | 923 | 923 | 4 | 12 | 0.004 | 0.013 |
| total | 2205 | 2225 | 38 | 18 | 0.017 | 0.008 |

The results show the effectiveness of our algorithm in detecting lanes with shadow interference. In addition, compared with other methods, the combined effect of the method proposed in this paper is better. The method of [6] has a better effect on the shadow interference elimination, but the extraction effect on the lane line is poor. The method [7] is found by experiments that filtering out the side of the lane direction may filter out the edge of the lane line and cause a higher miss detection rate.

## 5 Conclusion

We proposed an efficient and robust algorithm for detecting lanes with shadow interference. This method is called lane detection based on the vertical direction IPM sub-picture reconstruction and its hierarchical image fusion. The advantage of this method is that it can completely remove lane shadow interference, which is more thorough than other shadow processing methods. The reconstructed IPM image is a binary image and its background is extremely simple. So the lane line portion is obviously emerged. The background interference can be eliminated by simple threshold segmentation or contrast enhancement preprocessing, and the IPM map with only the extreme neighborhood of the lane line is obtained. This is the most ideal condition expected by the Hough transform algorithm. The two-stage IPM sub-picture fusion method (adding a Third-level sub-picture if necessary) can improve the robustness of the detection and is more reliable than obtaining the lane line position on the original picture alone.

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