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A Robust Lane Detection Method Based on Vanishing Point Estimation

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Abstract

Although lane detection technology has been developed for decades ,however, many challenging issues remain unresolved. In this paper, we propose a robust vanishing point-based lane detection method. Due to the perspective effect, the two parallel straight lines in 3-D space intersect at the 2-D plane. For the lane line extraction , we use lane shape features to extract lane lines . Firstly, we use LSD (line segment detectors) to extract the straight line segments in each frame of image. Secondly, we use a direction priority search method to remove the most of the interference information. This algorithm makes reference to the directional and shape features of lane lines in 2-D images. Finally, using the remaining straight line segments after filtering out the noise straight line to calculate the vanishing point of the lane line, we use a score function to remove non-candidate lane markings, the score function is constructed using the shape features, direction of the line segments. The experimental results show that the validity and robustness of our new algorithm under complex structured road scenes.

Keywords: lane detection; line segment detectors; vanishing point; direction priority search method; Vehicle Assisted Driving System;

1. Introduction

In recent years, the number of traffic accidents is on the rise[1]. These accidents are often caused by the driver's carelessness or fatigue, the vehicle deviates from its own lane. Lane detection is very important for vehicle assisted driving (including vehicle warning deviation system, vehicle lane change system, etc.) and autonomous guided

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vehicles[2]. With the rapid development of computer and machine vision, the method of lane detection based on machine vision has drawn the interest of scientists and scholars[3] .We have to extract lane boundaries from worn lane markings, various shades, lighting conditions and other external disturbances.

Vision-based lane detection can generally be divided into two categories: feature-based and model-based approaches. Feature-based methods generally use lane line width, edge, color, texture, and gradient features. Since these characteristic information of lane lines generally comes from the pixel level, this leads them to be more sensitive to noise such as various shades and different light intensity. Canny edge detection[4] uses gradient magnitudes to get edge information . The controllable Gaussian filter[5] uses the gradient direction information to extract the edge features. However, the thresholds for getting lane boundaries in these methods need to be manually set . This determines the method does not apply to a variety of scenarios. The model-based approach first chooses the right geometry for the lane. Model parameters were then calculated by Hough Transform (HT)[6-7], least squares or random sample identity (RANSAC)[8-9]. Although model-based approaches are effective for noise and lost data. However, because the model building a scene may not be suitable for other scenarios, they are not well adapted.

Inverse perspective mapping is also a new method of lane detection[10]. It converts 2-D images taken by the camera into 3-D image information. In 3-D images ,the lane lines are parallel and this feature is used to extract lane markings. However, the use of this method also has some disadvantages. Since its transformation matrix needs correction, it must be assumed that the road is flat. Otherwise it will lead to wrong detection. In addition, if there are obstacles on the road, the effectiveness of the map will be reduced.

Therefore, in order to extract the lane mark correctly, In this article, we use the shape and orientation features of lane lines extract the lane markings. LSD is different from other detection algorithms such as edge detection ,it is robustly and accurately extract lane lines under a variety of conditions. The direction priority search algorithm can effectively filter out most of the interference line segments through directional constraints. It can effectively reduce the estimation error of vanishing point. Obtain the dynamic ROI(region of interest) by calculating the estimated vanishing point to further narrow the extraction range of the lane line. In the ROI, we use a score function to calculate the lane markings in each direction through the vanishing point, and the lane mark in the two directions with the highest score as our lane mark.

The flow chart of this paper is shown in Figure 1.

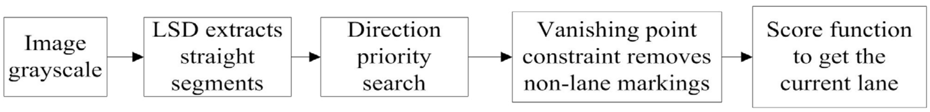


Fig. 1.The flow paper of this article

2. Lane detection algorithm

2.1. Image grayscale

For vision-based lane-line inspection systems, the source of the image data is captured by a vision sensor (CMOS or CCD camera) mounted in the windshield in front of the vehicle. The road image that is usually obtained using a vision sensor is an RGB color image. This paper uses lane shape features and directional features to extract lane lines. Therefore, the color feature information does not make any sense to us, and the amount of data is very large. In this paper, the obtained color image is converted into a grayscale image to facilitate subsequent processing of the image.

Common RGB color image grayscale method is as follows:

$$I(x) = 0.299R(x) + 0.587G(x) + 0.114B(x) \tag{1}$$

The above formula uses the traditional weighted average method. Lane line color is usually white or yellow, the road surface is gray. As a result, we use red and green channel information to expand contrast between lane markings and lane surfaces. In this paper we use the method in[11] to achieve grayscale RGB color images. The method is as follows:

$$I(x) = R(x) + G(x) - B(x) \tag{2}$$

The traditional method of gray-scale comparison with the method used in this paper is shown in Figure 2.

Fig. 2. (a) The original image (b)The traditional grayscale results (c) The method of this article

2.2. Feature Extraction

The traditional lane mark extraction line detection method is RANSAC algorithm and linear HT .However, the HT detection method has the disadvantages. First of all, since each valid pixel in the HT needs to be calculated and mapped into the parameter space, it will cause a large number of calculation processes, resulting in too much time consuming. Secondly, in the classical Hough transform, we want to determine whether a straight line exists or not, and only depends on whether the number of pixels on the line is higher than the previously defined threshold and does not confirm the existence of these intersections, resulting in false positive phenomenon. At the same time, the disadvantage of RANSAC is that the number of iterations is difficult to determine, and the points used are random.

The line segment detector (LSD) is proposed in[12]. It can extract the line segment structure in the image as a rectangular structure. They show that the LSD method is not only robust to noise but also fast .In their paper, we use the line segment detector to extract the line segment features for each frame of grayscale image. The LSD is a linear timeline segment detector that provides sub-pixel accurate results. It can process any digital image and not need to manually set any parameters. It is strong for line segment extraction in images. Because it controls the number of false detections well, there is only one error detection per image. The main process of this method is shown below:

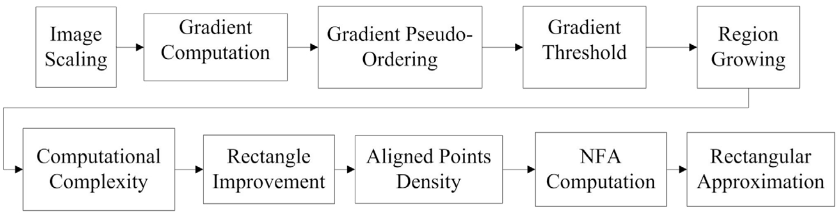


Fig. 3.LSD key steps

We evaluated the LSD performance using images under various interference conditions. The results are shown in figure 4.

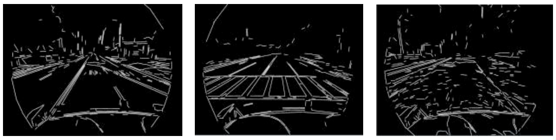


Fig. 4. First line: grayscale image; second line: LSD processed image

2.3. Noise filtering

The straight line segment extracted by LSD contains not only the lane markings but also the various non-lane line disturbances. We should save the lane markings and, at the same time, remove the non-lane markings as much as possible. In this section, we use a direction priority search algorithm to remove non-lane markings[13].

The current edge pixel (black square in Figure 5(a)) has 8 neighborhood pixels. However, considering the extending direction of the left lane line, only three neighborhood pixels are consistent with the connection characteristics of the left lane line edge pixels, as shown by the arrow in Figure 5(a). We define the priority of these three directions in the search process: the highest in the 45^{o} direction, the second in the 90^{o} direction, and the lowest in the 0^{o} direction. Right lane lines have similar properties, as shown in Figure 5(b).

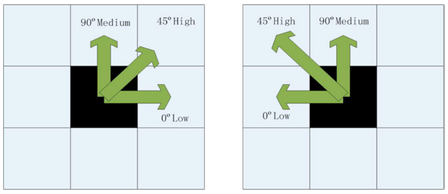


Fig. 5. Search priority rules Schematic diagram

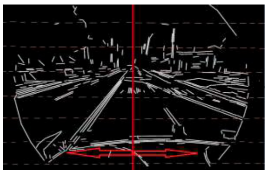


Fig. 6. Schematic diagram of the scan mode

As shown in Figure 6, First of all, Starting from the middle point of the bottom of the edge image to find the starting point of the edge pixels, from the middle to both sides and bottom to the top of the image scanning. If you have not traversed pixel, initialize it as connecting segments. Then, according to the connection characteristics of the pixel points on the left and right lane edges, the three neighborhood pixels of the starting pixel point are scanned based on the rule of the direction priority search, and the coordinates with the highest priority edge point are recorded. Finally, the scanned point in the neighborhood is connected with the starting point, and the edge point with the highest priority is taken as a new starting point. At the same time, the total number of edge pixel connections is recorded and until all the edge points are traversed. In order to avoid repeated scanning, the connected pixels are marked in the original image plane.

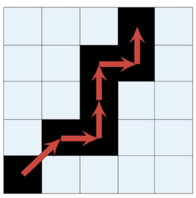


Fig. 7.pixel connection direction

After the scanning is finished, the recorded direction angle of the edge pixel connection is calculated, and the direction angle is the average value of the angles of the adjacent pixel connection lines. As shown in Figure 7, if the direction of the angle is not within the specified range of angles or the length of the connection is too small, it is considered the noise edge, which is directly filtered. The result is shown in the figure8.

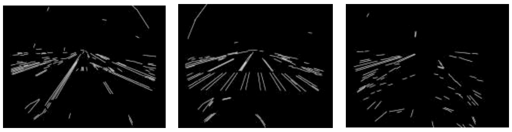


Fig. 8. Noise edge filtered image

2.4. Remove non-lane markings vanishing point constraints

Direction priority search filter straight line the straight line segment extracted by LSD. But only filters out non-lane markings that do not match the direction of the lane, There are still non-lane markings that have characteristics similar to lane lines. Therefore we further remove the non-lane markings by vanishing point constraints.

We first calculate the intersection of all the line segments. The vanishing point of the road exists in the intersection of these lines. In the real scene , since the lane lines and the edges of the road are nearly parallel, thus their projections will form dense intersection point cluster in the image plane. We define the location of the vanishing point by finding the peak point of intersection in these intersection clusters.

Let $V(x, y)$ represents obtained the vanishing point coordinate, and It is represented by the following formula:

$$V(x, y) = H(S) \tag{3}$$

Where $S = \{S_L, S_R\}$ is the lane line segment marks by direction priority search filter. The function of the function H is to extend the extracted segment set S and find out the position where all the line segments intersect the most point . That corresponds to the lane vanishing point location information.

After estimating the vanishing point, we find the vanishing line based on the abscissa of the vanishing point. Furthermore, since the bottom of the image is the hood of the vehicle, it is useless information. Therefore, we only need to get the lane line between the front cover of the vehicle and the disappearance line. The result is shown in the figure9.

Fig. 9. Region Of Interest

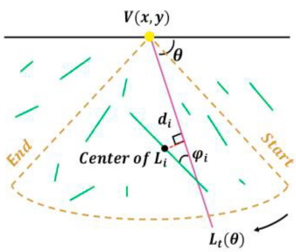


Fig. 10 .Remove non-lane markings vanishing point constraints

Below we further remove the non-lane mark on the ROI. As shown in picture 10.First, a test line $L_t(\theta)$ is defined as a line at an angle θ. It centers on the vanishing point and rotates clockwise at angle step of $\Delta(\theta)$, d_i is the shortest distance from $L_t(\theta)$ to a center point of L_i, φ_i is the acute angle between L_i and $L_t(\theta)$ .Finally, line segments are selected using the following constraints: $d_i < d_t$ and $\varphi_i < \varphi_t$, where d_t and φ_t are threshold values. Line segments that satisfy these constraints are selected as candidate line segments for lanes.

Inverse In practical applications, generally in the case of multiple lanes, we need more of the lane markings closest to the car. therefore, the score function is defined as follows[14]:

$$S_{L_t}(\theta)=\sum_{\mathrm{i}} \frac{l_i}{w_i}\exp(-d_i\sin(\varphi_i)) \tag{4}$$

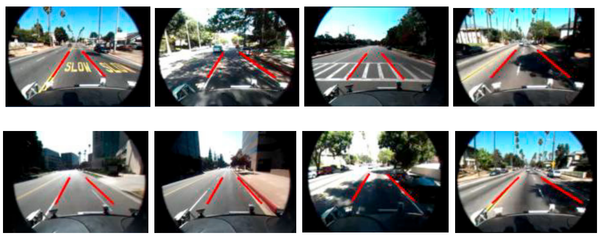
Where l_i is the length and w_i is the width of a line segment extracted by the LSD method . $S_{L_t}(\theta)$ has a higher value if d_i , φ_i and w_i have lower values or l_i has a higher value. Therefore, a high score value means that the probability of the overlap between $L_t(\theta)$ and Li extracted from the lanes is high. Then we can consider that a set of $L_t(\theta)$ with higher scores corresponds to lanes. The parameter values used in this experiment are $d_t = 2$, $\varphi_t = 10$.

3. Experimental results

We tested the proposed method using four data sets. They are given in[15].A total of about 1120 frames of data set .We used Matlab2014a to write and validate our algorithm. The PC used i5 processor at 3.4 Ghz. In order to effectively evaluate our algorithm, we use the correct detection rate, false detection rate and missing detection rate to represent the performance of the algorithm.

Table 1. The result of our algorithm's evaluation in Caltech lane data sets

Clips	Number of frames	Correct detection rate(%)	False detection rate(%)	Missing detection rate(%)
Cordova1	250	96.32	3.31	0.37
Cordova2	406	92.34	7.21	0.45
Washington1	337	92.58	6.92	0.50
Washington1	232	93.81	5.67	0.52



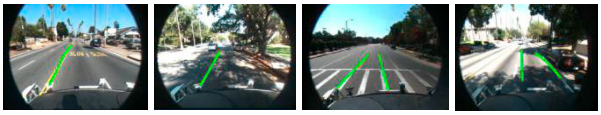


Fig.11. The first row : correct detection results by our method. The second row : false detection and missing detecting result by our method. The third row: correct detection and missing detecting results by Aly´s method.

As can be seen from Table 1 and Figure 11, our method correctly detects the lane line over 92%. It has strong robustness to various shades, text on the road, and zebra crossing. Overall, our algorithm has superior performance under a variety of conditions.. However, when there are obvious shadows or repaired marks of which orientations are similar to those of the lanes on the road, it will lead to test failure. From the third line of Figure 9, we can see that the Aly's method is not robust to complex shadows and zebra line fringes, resulting in erroneous detection of lane lines. Our algorithm can accurately detect lane markings under the same conditions because we use the lane edge information and shape features to extract the lane mark and vanishing point constraint methods to remove the interference.

4. Conclusion

In this paper, we propose a robust lane marking detection method based on vanishing point estimation .The method uses lane edge and lane segment as feature information to extract lane mark and vanishing point as restriction to eliminate interference line segment.

However, obvious shadows or repaired marks of which orientations are similar to those of the lanes, our algorithm can' t handle it well. In the future, we hope to solve this problem.

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