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A Multi-structure Elements Based Lane Recognition Algorithm

***Abstract**. The existing traffic lane recognition algorithms have the weaknesses of low recognition ratio, bad robustness and real-time, for overcoming these drawbacks, this paper proposed an algorithm of lane recognition based on multi-structure elements model of morphological. In the algorithm, the region of interest (ROI) is extracted from the original image, which is detected by the operator of Canny. After that, the lanes are extracted by the structure elements, which have similar characteristics to that of lane model. Several lines are detected by Hough transformation, and choose the parameters to reconstruct the traffic lane. The experiment results show that this algorithm is simple, has better robustness, and at the same time, can efficiently detect the lane mask accurately and quickly.*

***Streszczenie.** W artykule opisano metodę rozpoznawania linii na jezdni z poruszającego się pojazdu. Metoda bazuje na opracowaniu modelu morfologicznego multi-strukturalnego linii na podstawie danego obrazu oraz zastosowaniu transformaty Hough w celu wyznaczenia parametrów. Uzyskano w ten sposób zwiększenie szybkości w przypadku złożonego otoczenia, przy jednoczesnej niskim stopniu skomplikowania. (**Zastosowanie modelowania multi-strukturalnego w algorytmie rozpoznawania linii**).*

Keywords: lane detection; multi-structure elements model; region of interest (ROI)
Słowa kluczowe: wykrywanie linii, modelowanie multi-strukturalne, obszar zainteresowania.

Introduction

With the increasingly concerned about the rapid escalation of the road safety crisis, the intelligent vehicle technologies become hot researches. The intelligent vehicle technology is an important direction of Computer Vision. The visual system is the key part of intelligent vehicle technology, where lane recognition algorithm is the core part of assistant navigation in intelligent vehicle[1-3]. Much work has been carried out on vision-based lane recognition algorithm. Some of the early algorithms selected lane with special colours by the characteristics that they had obvious colour feature. At first, the algorithms established the lane model. Then they abstracted features again by its special geometry feature, size feature and shape feature. Finally, they got the lane marking lines with Hough Transform. But these algorithms were just suit to structured roads. It didn't work when the lane were blurry or in the complex environment.

In recent years, some new algorithms used the swing curve method, neural network method, deformation model method etc to recognize the lane [4-8]. But some of them had poor real-time performance because of huge calculation. Or the detected lane had pseudo-edges or been lost by some of the algorithms. The computer vision based lane recognition methods are usually affected by the illumination, rainy day, shadow, noise or the road conditions. Most lane recognition algorithms have the weaknesses of low robustness and huge calculation. Therefore, the highway without strong light, shadow or street lamps, was usually chosen by the existing lane recognition algorithm. According to the lane marking lines in different conditions, some researchers provided certain algorithms, but most of them had the weakness of bad robustness [8-12].

In order to solve the problems mentioned above, Youchun Xu improved a straight line based lane recognition method. This method could get good results by template matching method, but it had bad robustness in complex environment [13]. Tao Lei suggested a morphological structure element model based algorithm. This algorithm could accurately detected lane marking lines in different environment. But it adopted morphological gradient images, so it had the weakness of huge calculation and band real-time performance [14]. Therefore, this paper proposes a fast algorithm based on morphological multi-structure element model, this algorithm also combine with Hough transform to select parameters. This study preprocessed images by the performance that the morphology principle was simple and the calculation was less. Then it constructed multi-structure element with lane feature to select lines that were similar to lane model. After the Hough transform, it detected peak points to sign lane. The experiment results show that this algorithm can work for roads with different qualities in variety of complex environments.

Extraction of ROI

In the road images, much information is unavailable. By selecting the region of interest (ROI), the algorithm can reduce the running time and predigest the process. The ROI is shown in Fig.1.

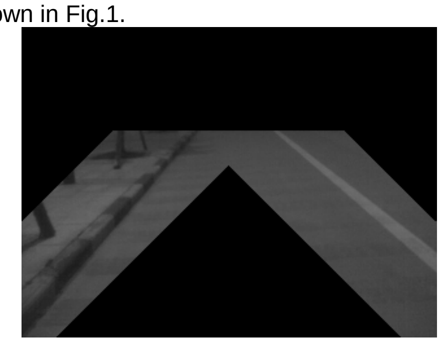


Fig.1 ROI

In fig.1, the region besides the part is the ROI (Region of Interest). The lane recognition algorithm just processes this part. In order to improve the real-time capability, the algorithm can also use the method that changes the size of ROI dynamically. If the result is reliable, the algorithm can reduce the size the ROI. In contrast, the algorithm need enlarge the ROI to enhance the reliability.

Lane detection

After abstract the ROI, the algorithm should detect the edge of the lane. There are two main algorithms to detect edge, one is the entropy based method and another is the classical edge detection operator based method. The former is simply and little effected by the environment. Meanwhile, it would lose much edge information. It doesn't work for images with complex background and blurry lane marking lines. It is just suit to the images with structured road and images that there is obvious difference between the road gradation and the background gradation. So we adopted classical operator based edge detection method. In order to enhance the robustness of the algorithm, we proposed a novel model based on the morphological multi-structure elements.

A. Edge detection

The edges of the lane have the characteristics that they are sharp and unbroken in perfect condition, and they are weak in challenging environments, such as in the condition of strong light, rainy days or night time. Thus, an operator with good edge detection capacity has to be chosen. By analyzing the existing edge detection operator, we would find that the Canny operator has good weak edge detection capability. In the detection process, the operator uses the Gauss filter which has specified standard deviation σ to reduce the noise in the image at first. Then it searches the ridge and top part in gradient image to detect weak pixels set. In this study, we used Canny operator to detect the edge of lane marking lines. In Fig.2, there are four lane images captured in different environments, the problems which have to be solved are shown as follows:

Canny operator is good at weak edge detection. While entirely detecting the lane edges, it also gets more other edges. It is a hard work to eliminate non–lane structures.

The edges of lanes in good condition are easy to extract. Nevertheless, the lanes in the condition of rainy times, night times, trees shadows, or seriously polluted, the edges would not be abstracted easily.

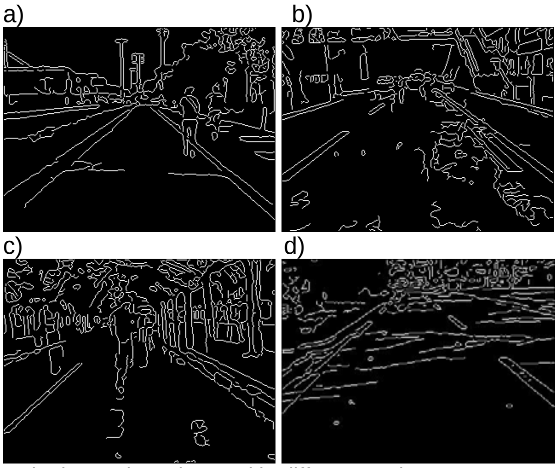


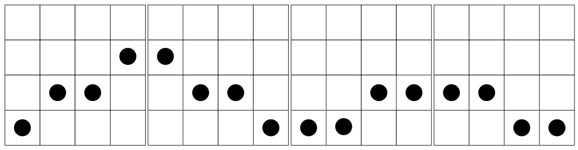
Fig.2 The lane edges detected in different environments

B. Morphological multi-structure elements model

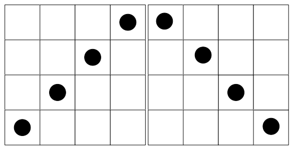
In allusion to the problem that the more extracted edges are pseudo edge, this paper proposed a lane detection method based on morphological multi-structure elements model. Because of the advantages in structure elements modeling, the morphology plays an important role in image feature extraction. The lane structures are straight lines or approximate to straight lines, which are clearly different from the non-lane structures. So by using the features of the morphological multi-structure elements model method, we can resolve the problem mentioned above efficiently.

By analyzing the characteristics of the left and right lane marking lines, we would find the visual effect of the parallel lines is that the lines are at an angle. In real road condition, the slopes of the lane marking lines can be fixed in a certain range. The slope would change if directions of the camera or the car change, the angle can keep within the range from 15°to 75°. In this way, the problem of lane abstraction becomes the straight lines detection, the slope of which is from 0.2679 to 3.7321. In digital image, straight line is the collection of some pixels. The straight line can be decomposed to the set of several different structure elements. Several lanes in complex environments are decomposed to structure elements, the results are shown in fig.3.

a) Little angle structure elements B_{l1}、B_{r1}、B_{l2} and B_{r2}



b) Standard angle structure elements B_{l3} and B_{r3}



c) Big angle structure elements B_{l4}、B_{r4}、B_{l5} and B_{r5}

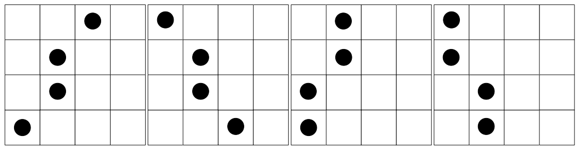


Fig.3 Left and right lanes structure elements models

In fig.3, B_{l1} 、 B_{l2} 、 B_{l3} 、 B_{l4} and B_{l5} are the elements of left lane marking lines, B_{r1}、B_{r2}、B_{r3}、B_{r4} and B_{r5} are elements of the right lane marking lines. The edge characteristics of the non-lane are shown in fig.4 (The non-lane edges are the edges of tree shadows, seeper, lights, green belt, barrier etc.)

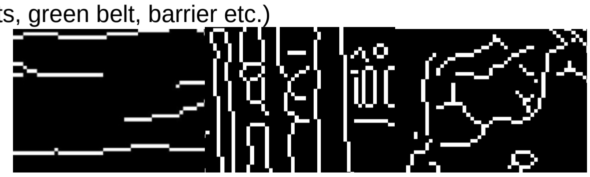


Fig.4 The edges of non-lane

The steps that remove the non-lane edges are shown as follows:

(1)For the non-lane without the lane structure elements model features, we do opening and closing operation on lane structure elements to abstract framework, the edges of non-lane would be removed.

(2)For the non-lane with the lane structure elements model features, we use region segmentation to remove the non-lane edges.

C. Lane structure elements abstraction

In order to reserve the lane marking lines and exclude the non-lane lines, we used the morphological filtering theory [15-17]. We did binary filtering for edge images based on the existing structure elements with the lane features. The purpose was to remove the image structure without the lane features. So the lane structure would be reserved. It was done for the subsequent Hough transformation. Not only was the Hough transform accuracy, but also the calculation became simple. Concrete steps of lane abstraction are shown as follows (Suppose g is lane image, E_{li} is the left lane elements, B_{ri} is the right lane elements, $1 < i < 5$):

Abstract the left and right lane with the multi-structure elements:

(1) $$L_i = g \circ E_{li} \bullet E_{li}$$

(2) $$R_i = g \bullet E_{ri} \circ E_{ri}$$

The abstracted left and right lane marking lines are shown as follows:

(3) $L_L = L_1 \bigcup L_2 \bigcup L_3 \bigcup L_4 \bigcup L_5$

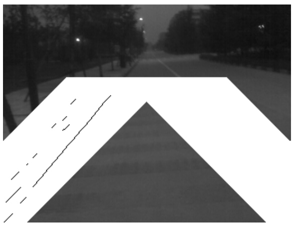
(4) $L_R = R_1 \bigcup R_2 \bigcup R_3 \bigcup R_4 \bigcup R_5$

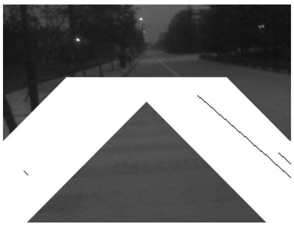
The feature of the lane is described by the equation:

(5) $L_L = L_1 \bigcup L_2$

Abstract the lane structure elements of the fig.1 by the equation (1) -（5）. Fig.5 shows that doing binary filtering with multi-structure elements can effectively abstract the lanes and remove the image structure without the lane features. Meanwhile, it predigests the subsequent Hough transform.

a) L_L results b) L_R results





c) L results

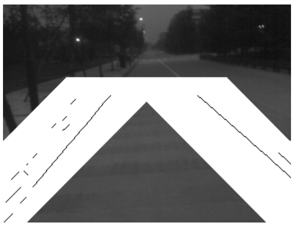


Fig.5 The lane edges

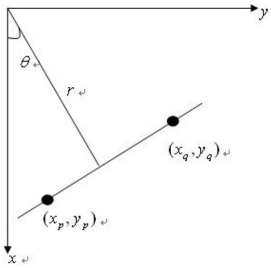


Fig.6 The parameterization of the lane on xy planes

After filtering the lane image, do Hough transform on the image. The parameterization of the lane on xy planes is shown in fig.6.

By Hough transform, we suppose a straight line as follows:

(6) $Y = ax + b$

In the polar coordinate systems it can be expressed as follows:

(7) $r = x\cos\theta + y\sin\theta$

Where,

(8) $r = \sqrt{x^2 + y^2}$

The parameter r represents the normal distance between the line and the origin. The parameter θ is the angle between normal and x axis. It is obvious that a straight line in image space mapped into the parametric space is a point, and that a point in parametric space is a straight line in image space. In the program, quantize the parameters x and θ to small blocks in the prior estimated change intervals. Work out each r with the quantization value by substituting r with each (x, y) point. The obtained values are distributed into the small blocks. If a value is located in a block, the accumulator of the block will plus 1. After transforming all the (x, y) points, check the accumulator of each block, we would get the block whose account value is the maximum. The corresponding (r, θ) of this block can be considered as a detected straight line. But after the Hough transform, we would get many lines with the straight line features, so how to screen out correct lane marking lines is an urgent problem should be settled.

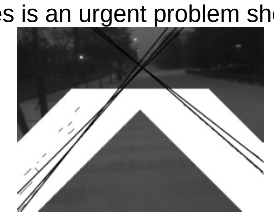
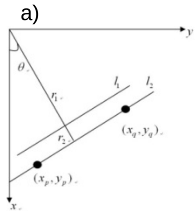


Fig.7 The result after Hough transform

a) b)



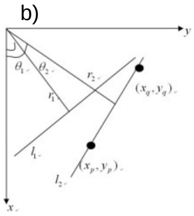


Fig.8 r and θ selection

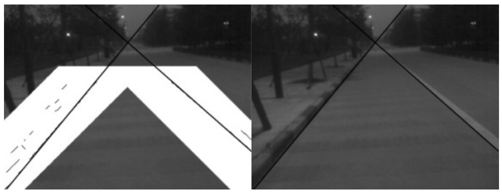


Fig.9 The lane reconstruction after r and θ selection

After the Hough transform, we would get the parameters l、r and θ of the straight lines, where l is the length of the straight line, r is the distance between the origin and the straight line, θ is the angle between the normal and the y axis. Determine the actual lane by selecting the parameters r and θ. By concluding the factors that affect the lane abstraction, the principle of selecting parameters r and θ is shown as follows:

(1)One feature of the lane is that it has a certain width, and the detected lanes are two straight lines approximately parallel. So the inside line must be marked. When the θ value of each line is the same, the requirement for r is the least. The feature is described in fig.8 (a).

(2)For the green belt or other things nearby the lane, the feature is that the lane is on the inner side all the time. When the r values of each line are different, the parameter θ is the maximum. The feature is described in fig.8 (b).

By the principle of selecting parameters r and θ, the recognized lanes are shown in fig.9.

Results and analysis

The experiment platform of the algorithm is a minibus. The CCD was fixed on the central position of the minibus front windshield. The computer was chosen the ordinary Intel(R) Pentium(R) Dual 3.0GHz, 4GB of memory. The size of the captured city road video image was 320×240 and the gray scale was 256. The actual city roads are usually with the situation that poor quality, changing environments (daytime, night time, rainy day and etc), clutter background. Hence, the algorithm must be good robustness. The experiments got good results for a variety of roads in multi-conditions. The results are shown in fig.10.

Fig.10 The results for a variety of roads in multi-conditions

Throughout the process of the algorithm, Hough transform is the most time consuming step. Reducing the number of the straight lines would directly impact the performance of the Hough transform. Table.1 shows the consuming time of the algorithm in this paper, in paper [13], and in paper [14]. The contrast results show the high real-time property of this algorithm.

Table 1 The consuming time of the algorithm（Unit：s）

The method	Good condition	Rainy day	Night time
Paper 13	0.1739	0.1774	0.1831
Paper14	3.8762	3.9918	4.1270
This paper	0.1061	0.1125	0.1174

The experiment results in Table.1 show that this algorithm spent the less time than other two algorithms. The reasons are shown as follows:

(1)The size of the original image was 240×320, while the size of the ROI was 240×320-90×320-264×132/2=0.3981. So the real-time property of the algorithm enhanced the 2.5118 times of before.

(2)The morphological multi-structure elements filter filtered all the non-lane structure pixels. This step reduced the search points, so it greatly reduced the running time of the algorithm.

The experiment results in fig.10 and table.1 shows that this algorithm did quick lane recognition while being good robustness.

Conclusions

This paper proposed a fast algorithm of lane recognition based on multi-structure elements model of morphological. It mainly in view of the actual situation that the city road surfaces are complicated and the city roads are greatly affected by the environment to solve the problems that weak real-time and robustness property in traditional algorithms. The experiment results show that this algorithm can recognize the lane marking lines quickly and accurately in variety of complex environments, which also indicates that this algorithm has good real-time and robustness property.

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