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Lane Detection Algorithm at Night Based-on Distribution Feature of Boundary Dots for Vehicle Active Safety*

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Abstract: This study introduces a novel detection algorithm to recognize the lane markers on a structured road at night. The proposed algorithm utilizes neighborhood average filtering, Sobel operator and threshold segmentation of maximum entropy to preprocess the original image. Combining gray level image and edge image obtained by Sobel operator, we analyze the distribution feature of lane boundary dots at night and sort the boundary dots into 4 sets. Then, multiple-direction searching method is carried out to eliminate the false lane boundary dots. Final, we use adapted Hough transformation algorithm to obtain the feature parameter of the lane edge. The proposed method is proved to be reliable and robust in outside environment through experiments for the various kinds of images.

Key words: Lane detection, Hough transformation, edge feature dot, computer vision, pattern recognition

INTRODUCTION

According to the traffic departments' statistics, 90% of traffic accidents are caused by error operations or distractions, such as getting phone calls, driving fatigue, inattention and so on. These cause the vehicle deviate from the normal driving lane and lead to the occurrence of major traffic casualties (Dagan *et al*., 2004). Now, with the growing number of private cars in China, the research on active safety technology of lane marker detection is more important than ever before.

Now, Europe, America and Japan have thrown themselves into part lane detection system. Some systems, such as the RALPH system (Bertozzi *et al*., 2002), AutoVue system (Iteris, 2000), Start system (Lee *et al*., 1999), AURORA system (Chen *et al*., 1995) and ALVINN system (Pomerleau *et al*., 1997), are representative systems. In these systems, they mostly use different models and road edge extraction technology to do the lane detection. Some use vision-based technology to detect lane marker.

Up to now, a numbers of vision-based lane detection algorithms have been presented. They usually use different lane patterns (solid or dash white painted line, etc.) or different road models (2 or 3D, straight or curve) and different techniques (Hough, template matching, neural networks, etc.). There are two methods utilized in lane detection: the feature-based and the model-based method. The feature-based method positions the lanes' images by detecting the obvious features, such as lane edges (Broggi and Berte, 1995; Bertozzi and Broggi, 1998; Kaske *et al*., 1997; Broggi, 1995; Yu *et al*., 1992) or painted lines (Beucher and Bilodeau, 1994; Zhang, 2002), etc. This method requires well-painted lines or visible lane edges in images acquired from CCD. Furthermore, it does not impose any global constraints on the lane edge shapes, this method may suffer from occlusion or noise. In addition, some researchers use mathematical morphology instead of Robert operator and Sobel operator. Trung-Thien, Hyo-Moon Cho and Sang-Bock Cho use the method that horizontal line and sub-region are firstly detected and then use K-means clustering algorithm to classify left and right lane cluster (Tran *et al*., 2011).

However, these detection algorithms have their disadvantages. These algorithms are just available during daytime in which light intensity is strong and light ray is relatively even, but it does not work properly at night. The algorithms lack the adaptive ability to deal with the change of light.

This research studies the imaging characteristics of the road at night and analyzes distribution features of the boundary dot in order to recognize the lane marker at night. Image preprocessing and recognition of road markers build up the road markers detection algorithm in this study. This algorithm adopts neighbor average filtering to suppress image noise, applies the algorithm based on Sobel operator to enhance road edge and then

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uses the maximum entropy algorithm to segment the acquired road image. For road marker recognition, we analyze the distribution features of road boundary dots which use the 2D linear model and then apply the improved Hough transformation to identify lane markers at night.

DETECTION ALGORITHM OF HIGHWAY MARKER AT NIGHT

Our study focuses on nighttime highway lane markers which have the following characteristics:

- After the lane markers are imaged, the view of lane markers is different from their backgrounds
- The lane width is usually 3.5~4.5 m, so its imaging has obvious geometric characteristics
- Traveling vehicle lane marker is a continuous or regular interruption lane line
- To meet the speed requirements of the highway, the road usually has a good linearity and road markers can be considered as a straight or nearly straight line

Characteristics of night image: Compared with the imaging during the daytime, night imaging has its own characteristics:

- The main light source driving at night is lamp lighting, street lighting and so on, but the light intensity is weak; the overall gray value of original image from CCD camera at night is much lower than that value during the daytime. The contrast ratio between the road lane marker and road surface is low and the road boundary features are not very clear
- Because of a variety of lightings, the ground appears with alternating light and dark spot area and the distribution of image ray value of the road is uneven. So, we will find that gray value is higher near the bottom of the image, but is low away from the bottom of the image
- There may be a lot of large area lighting billboards or traffic signage with a reflective coating on the roadside which all have a great impact on imaging

Preprocessing of night road image: As shown in Fig. 1, the specificity of imaging at night increases the difficulty of road marker recognition and this makes its recognition method different from the image processing method which has a good result for images that derived from daytime.

Neighbor average filtering: Most of the noise caused by the sensors, transmission channels and quantization, are almost random. Their impacts on a pixel can be seen as isolated; therefore, the gray value of the noisy point will be significantly different from the value of the near points (Pomerleau *et al*., 1997).

Fig. 1: Original lane image

Fig. 2: Image processed by neighbor average filtering

Based on above analysis, this study uses neighbor average filtering to eliminate noise. Shown as Eq. 1, f(x, y) is the pixel value that the horizontal coordinate of this pixel is x and the vertical coordinate is y. S is an area that contains dot (x, y) and its range is 3×3. M's value is 9. Figure 2 shows lane marker image after neighbor average filtering:

$$g(x,y)=\frac{1}{M}\sum_{(x,y)\in s} f(x,y) \tag{1}$$

Extract road boundary based on Sobel operator: Edge is the most basic image feature; it exists in the target and background, target and target, region to region, the primitive and the primitive:

$$\begin{aligned} S_x = &[f(x-1,y+1)+2f(x,y+1)+\\ &f(x+1,y+1)]-[f(x-1,y-1)\\ &+2f(x,y-1)+f(x+1,y-1)] \end{aligned} \tag{2}$$

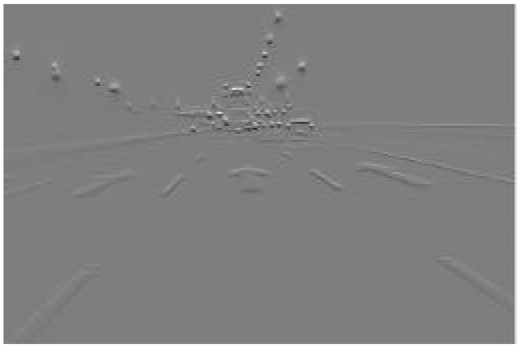

Fig. 3: Edge image by horizontal Sobel operator

Fig. 4: Edge image by vertical Sobel operator

$$S_y = [f(x-1,y-1)+2f(x-1,y)+ f(x-1,y+1)]-[f(x+1,y-1) + 2f(x+1,y)+f(x+1,y+1)] \quad (3)$$

$$S=\sqrt{S_x^2+S_y^2}\approx|S_x|+|S_y| \quad (4)$$

$$\tan\alpha\,(x, y) = S_y/S_x \quad (5)$$

Sobel operator is one kind of first differential operator. The operator calculates direction and partial directional derivative on the area that f(x, y) is the center and its neighbor region is 3×3 according to Eq. 2. S has two important physical quantities, as shown in Eq. 3 and Eq. 4. Figure 3 and 4 are rendered images that are enhanced by Sobel operator.

Threshold segmentation of the maximum entropy: In this study, we use the maximum entropy algorithm to partition image. If T is the final segmentation threshold, pixels that image gray value smaller than T is the background area and pixels that image gray value bigger than T is the road area. Take frequency of regional B and L as the gray-level

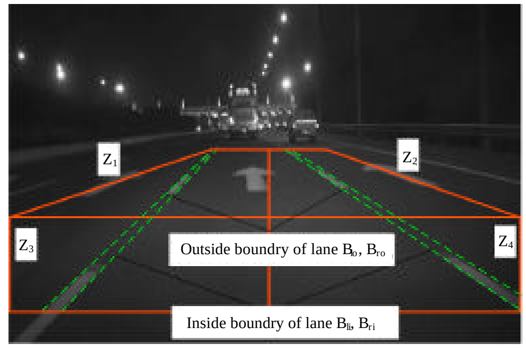

Fig. 5: Image searching area and definition of inside and outside boundary of lane

probability p, then the probability of regional B and L, respectively are p_L and p_B:

$$p_L=\sum_{i=T}^{255}p(i), i\in[T,T+1,T+2,\cdots,255]$$
$$p_B=\sum_{i=0}^{T-1}p(i), i\in[0,1,2,\cdots,T-1] \quad (6)$$

Define entropy of region B and L as follows:

$$E_L(T)=-\sum_i(p(i)/p_L)\times\lg(p(i)/p_L),\quad i\in[T,T+1,T+2,\cdots 255]$$
$$E_B(T)=-\sum_i(p(i)/p_B)\times\lg(p(i)/p_B),\quad i\in[0,1,2,\cdots,T-1] \quad (7)$$

Define entropy of image as:

$$H(t)=H_L(t)+H_B(t) \quad (8)$$

When the Eq. 8 reaches to the maximum value, correspondingly, T is the segmentation threshold we need.

Road detection based on boundary characteristic: In order to reduce the impact of light on the recognition of lane marker, our method divides the search range of lane marker into four regions Z_i i = 1, 2, 3, 4. Define the following boundary set: left outer boundary set B_{lo}, left inner boundary set B_{li}, right outer boundary set B_{ro} and right inner boundary set B_{ri}, shown in Fig. 5.

If current pixel is f and its location in image is (x, y) to calculate the following Eq.:

$$E=\sum_{i=x+1}^{x+n}w_i f_i-\sum_{i=x-n}^{x-1}w_i f_i \quad (9)$$

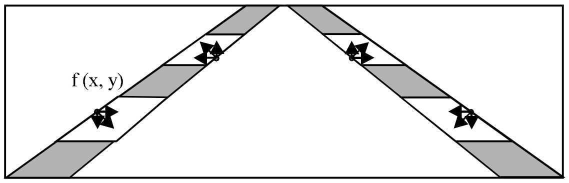

Fig. 6: Searching orientation of false boundary dots

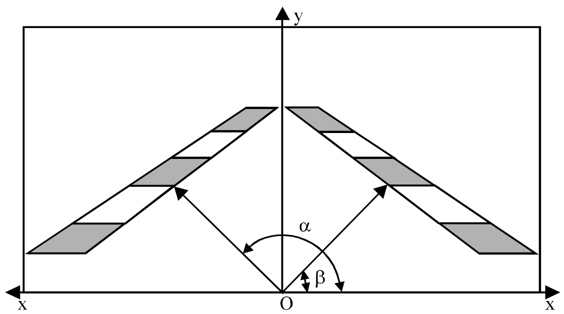

Fig. 7: Coordinate system for Hough transformation

n is the number of pixels which participate in computing in Eq. 9, f_i is the horizontal gray value of current pixel f(x, y), w_i is the weight which is related to the distance to f and the farther the distance, the smaller the weight. When f is a boundary point, the absolute value of E should be greater than or equal to a constant. On the basis of above, our algorithm will classify each boundary point according to the texture characteristics of the road boundary into the following categories:

For the road boundary dots on the left plane:

- 1.If $E \geq C_x \cap S_x > 0 \cap S_y > 0$, then $f(x, y) \in B_{lo}$
- If $-E \geq C_x \cap S_x < 0 \cap S_y < 0$, then $f(x, y) \in B_{li}$

For the road boundary dots on the right plane:

- If $E \geq C_x \cap S_x > 0 S_y < 0$, then $f(x, y) \in B_{ri}$
- If $-E \geq C_x \cap S_x < 0 \cap S_y > 0$, then $f(x, y) \in B_{ro}$

Former method may misclassify the road boundary feature points resulting in false boundary points. For this case, in our study, we apply multi-directional search method to deal with. Take the pixels f(x, y) in the left outer boundary set B_{lo} as an example, if f(x, y) is a true boundary point. Place the boundary points as the basic points to search lane width distance d further along the vertical, horizontal and diagonal direction and we can find the corresponding points in the right inner boundary set B_{lo}; if we cannot find, we believe that f(x, y) are the wrong boundary points and remove these dots from boundary

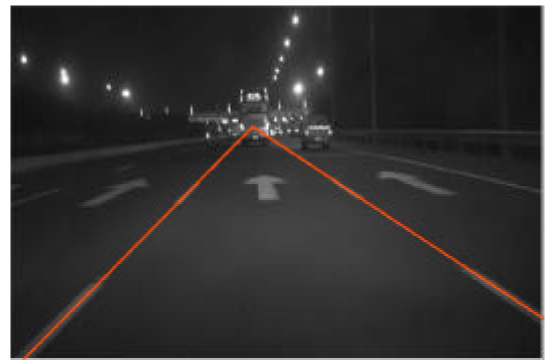

Fig. 8: Detection result for lane marker at night

set. Similarly, for all points in the right outer boundary set B_{ro} and right inner boundary set B_{ri}, we search and determine whether all these dots in boundary set meet the requirements according to the search direction shown in Fig. 6.

Road marker recognition based on Hough transformation: In this study, we select linear model as the lane marker model and use Hough transformation to recognize lane boundary. The coordinate system established shows in Fig. 7. Take the midpoint of the bottom edge as the origin, the right horizontal direction as the positive x axis and vertical upward direction as the positive y axis.

In order to improve computational efficiency, give the following search premise:

- Left lane is on the left half-plane of the image and the right lane is on the right half-plane of the image. Therefore, in the process of lane detection, the image is divided into two parts. Left and right road boundary is recognized, respectively
- The angle between left and right lane boundary and the x axis are, respectively α and β. The calculation range of α and β will be, respectively restricted to 90°~180° and 0~90°
- Below the image of lane line, we begin to search down from the 1/3 height of lane line image in order to reduce the detection time. Detection result for lane marker at night are given in Fig. 8

EXPERIMENTAL CONDITIONS AND RESULTS ANALYSIS

Experimental hardware includes black and white CCD camera, data lines, embedded computers, LCD monitors, image acquisition card, car power, voltage regulator and sound box. Black and white CCD camera is mounted on the rear of front windshield. CCD center axis parallels to the vehicle longitudinal axis. CCD camera's model is the German Basler 601f, capture resolution is 320×240. The lens is Japan Seiko lens and focal is 8.5 mm.

The preceding method is tested in visual C++2005 programming platform. First, convert the color image to gray level image and apply neighbor average filtering to reduce image noise. Second, use Sobel operator to obtain the road boundary enhancement image and use the maximum entropy method to partition the image. Divide image search area on the basis of image pre-processing and combine the boundary image with the gray level image and analyze the characteristics of the road boundary at night in order to put forward the method that discriminates false road boundary points. Finally, apply the improved Hough transformation to recognize lane marker. Verified by our experiment, in the condition of the night, our recognition algorithm can better recognize road lane marker. The average time spend on the recognition is 65 m sec and the accuracy is 98% or more. The characteristic of real-time is better.

CONCLUSIONS

In this study, we model lane marker as linear and adopt neighbor average filtering, enhanced road boundary, road image partition and other preprocessing method to deal with lane image. Combine road boundary image with gray-scale image to analyze the texture characteristics of the road boundary and use improved Hough transform to realize the road lane detection. The recognition algorithm takes an average of 65 msec in the programming platform of visual C++2005. The algorithm presented in this study is verified to be effective and especially the real-time characteristic is prominent.

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