An Adaptive Approach to Lane Markings Detection

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***Abstract*—A novel algorithm is represented to determine the position of markings in the presence of distracting shadows, highlight, pavement cracks, etc. RGB color space is transformed into $I_1I_2I_3$ color space and I_2 component is used to form a new image with less affection of the clutter. Using an improved edge detection operator, an edge strength map is produced and binarilized by adaptive thresholds. The binary image is labeled and circularity of all connected components is calculated. The Self-Organizing Maps is adopted to extract regions that imply potential markings. Finally the position of markings is obtained by curve fitting. Here color information is utilized fully and all thresholds are set adaptively. The method based on circularity of connected component shows its outstanding robustness to lane markings detection and has a wide variety of applications in the areas of vehicle autonomous navigation and driver assistance system.**

***Index Terms*—Circularity, Color space transformation, Intelligent vehicle, Lane detection**

I. Introduction

A challenging task of future intelligent vehicle is road following. It includes lane detection (which mainly studies the localization of the road, the determination of the relative position between vehicle and road, and the analysis of the vehicle's heading direction) and obstacle detection (which mainly studies localization of possible obstacles on the vehicle's path). Lane detection is the problem of locating lane boundaries without prior knowledge of the road geometry. More generally, however, lane detection has been reduced to the localization of specific features such as markings painted on the road surface. This restriction eases the detection of road. Nevertheless, two basic problems must be faced.

Firstly, the presence of highlight and shadows (projected by trees, buildings, bridges, or other vehicles) produces artifacts onto the road surface and changes the normal road texture. Secondly, other vehicles on the path partly occlude the visibility of the road and therefore of road marking as well. Recently, many road marking detection methods have been developed for vehicle navigation. Unfortunately, these techniques either incur heavy computing overloads or the environment has to be very well defined. It is also observed that other useful criteria are seldom considered. In this paper, an adaptive lane detection method based on the discrimination of circularity of connected components is proposed. Firstly, the RGB color space is transformed into $I_1I_2I_3$ color space and I_2 component is normalized to form a gray image that is called I_2 image. Secondly some masks are used to detect vertical edges of I_2 image to form an edge map. Edge map is binarilized by adaptive thresholds set according to local maximum value of pixels. After the binary image being labeled, circularity of each connected component is calculated. By self-organizing maps, all values of circularity are classified, and accordingly, lane marking is extracted from image adaptively. Finally, curve fitting is applied to lane marking.

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II. Color Space Transformation

RGB is the most commonly used model for the television system and pictures acquired by digital cameras and suitable for color display, but not good for color scene segmentation and analysis because of the high correlation among the R, G, and B components[1][2]. Also, the measurement of a color in RGB space does not represent color differences in a uniform scale and hence it is impossible to evaluate the similarity of two colors from their distance in RGB space. Ref. [3] performed systematic experiments of region segmentation to derive a set of effective color features as follows:

$$\begin{aligned} I_1 &= (R+G+B)/3 \\ I_2 &= (R-B)/2 \\ I_3 &= (2G-R-B)/4 \end{aligned} \qquad (1)$$

Comparing $I_1I_2I_3$ with other color spaces (RGB, YIQ, HIS, Nrgb, CIE, XYZ, CIE(L*u*v*), and CIE(L*a*b*), Ref.[3] claimed that $I_1I_2I_3$ was more effective in terms of the quality of segmentation and the computational complexity of the transformation. In many road scenes, intensity is not enough to differentiate lane marking due to shadows, puddles, pavement cracks, highlight, etc, but I_2 can do this very well. For these reasons, we adopt I_2 component of this color space. Since I_2 may be negative, in order to understand I_2 image intuitively, it is normalized as follows:

$$V(i,j) = \frac{I_2(i,j) - \min(I_2)}{(\max(I_2) - \min(I_2))} \qquad (2)$$

where

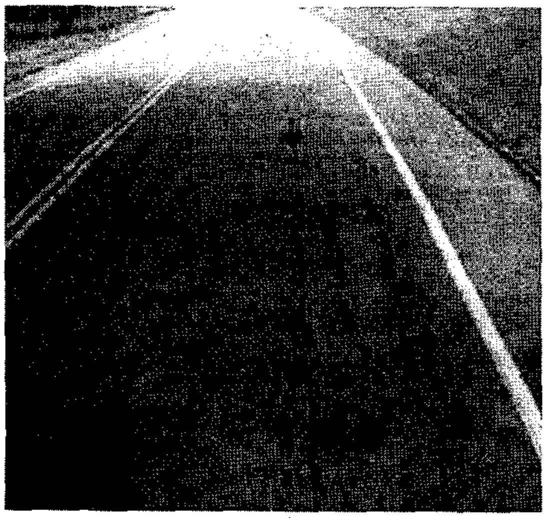
$V(i,j)$ - gray level value in I_2 image;

$I_2(i,j)$ - value of I_2 component of pixel (i,j) in $I_1I_2I_3$ color space;

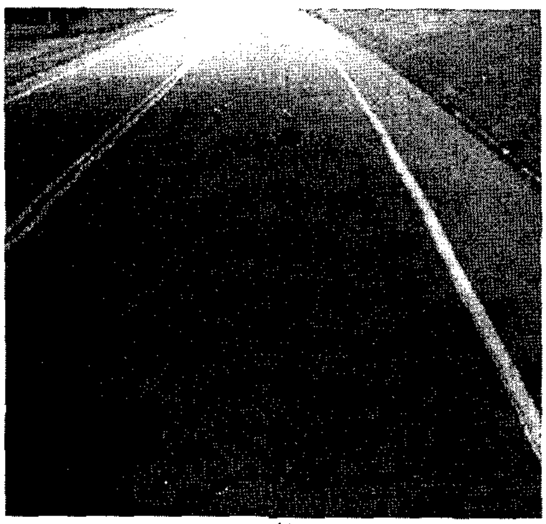
$\max(I_2)$ - maximum of I_2 among all pixels ;

$\min(I_2)$ - minimum of I_2 among all pixels;

Thus a so-called I_2 image appears (Fig.1, (a) Original image (b) Intension image of RGB (c) Normalized I_2 image. It can be easily found that contrast between lane marking and road in (c) is more distinct than that in (b), and disturbance of shadows and highlight is weakened.).



(a)



(b)

(c)

Fig. 1. Comparison between intension image and I_2 image

III. Edge Detection

In most case, orientation of lane marking is extended upward. Inspired by Sobel edge detection operator, a novel operator consisting of five masks to detect edges of lane marking is introduced in the paper. These masks are denoted in expressions (3)-(6).

$$h_1 = \begin{bmatrix} -1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & -2 & 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & -3 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & -2 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 & 1 \end{bmatrix} \quad (3)$$

$$h_2 = \begin{bmatrix} 0 & -1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & -2 & 0 & 2 & 0 & 0 \\ 0 & 0 & -3 & 0 & 3 & 0 & 0 \\ 0 & 0 & -2 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 & 1 & 0 \end{bmatrix} \quad (4)$$

$$h_3 = \begin{bmatrix} 0 & 0 & -1 & 0 & 1 & 0 & 0 \\ 0 & 0 & -2 & 0 & 2 & 0 & 0 \\ 0 & 0 & -3 & 0 & 3 & 0 & 0 \\ 0 & 0 & -2 & 0 & 2 & 0 & 0 \\ 0 & 0 & -1 & 0 & 1 & 0 & 0 \end{bmatrix} \quad (5)$$

Additionally, h_4 and h_5 is symmetric to h_1 and h_2.

$$h = \sqrt{h_1^2 + h_2^2 + h_3^2 + h_4^2 + h_5^2} \quad (6)$$

With this operator, a new edge map representing edge magnitude is illustrated in Fig. 2.

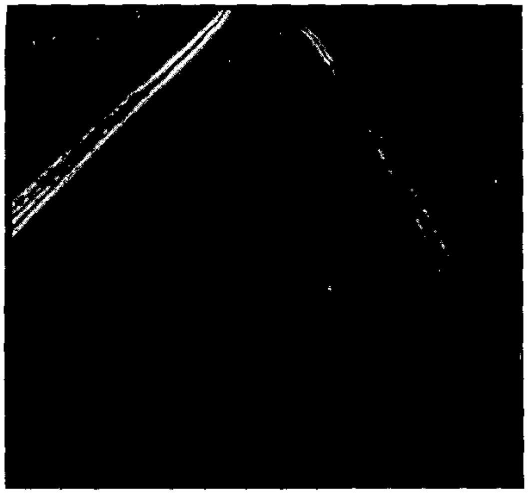


Fig.2. Edges map of I_2 image

In order to identify marking feather, the edge image must be binarilized. Due to different conditions, constant threshold seldom gives satisfying results in edge detection. So the binarilization is performed by adaptive threshold

$$e(i,j)=\begin{cases}1, \text{if } h(i,j)\geq m(i,j)/k \\ 0, \text{ otherwise}\end{cases} \qquad (7)$$

where $h(i,j)$ represents the value of pixel(i,j) in edges image, $m(i,j)$ represents the maximum value in a given window and k is a constant. The window is illustrated in Fig.3 and the result of the binarilization of edge map is illustrated in Fig.4, considering $k=2$.

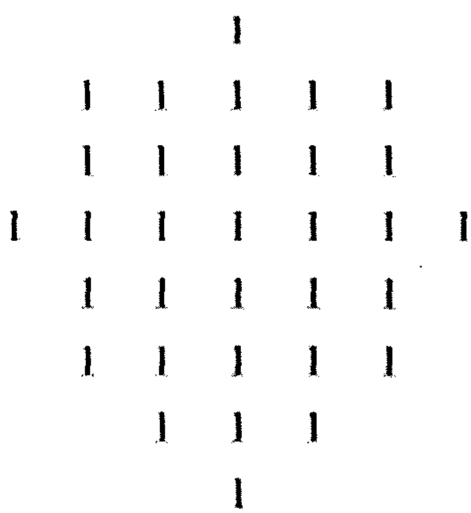


Fig.3. Window used to calculate local maximum of edge magnitude

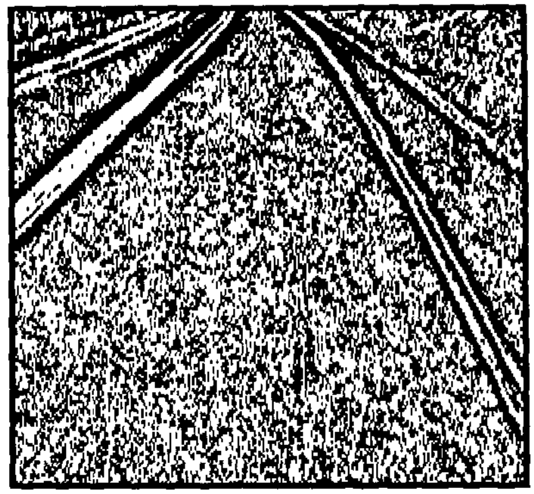


Fig. 4. Binarilization of edges map

IV. SHAPE DESCRIPTOR

The binary image consisting of connected components in Fig.4 is labeled [4] in order to extract lane marking.

Circularity is the feature defined by all pixels on border of region R

$$C=\frac{\mu_R}{\sigma_R} \qquad (8)$$

where

μ_R and σ_R is the mean and MSE of distance between center of gravity and border of region R, respectively.

$$\mu_R=\frac{1}{K}\sum_{k=0}^{K-1}\left\|(x_k,y_k)-(\bar{x},\bar{y})\right\|$$
$$\sigma_R=\frac{1}{K}\sum_{k=0}^{K-1}\left[\left\|(x_k,y_k)-(\bar{x},\bar{y})\right\|-\mu_R\right]^2 \qquad (9)$$

where

$$\bar{x}=\frac{1}{A}\sum_{(x,y)\in R}x$$
$$\bar{y}=\frac{1}{A}\sum_{(x,y)\in R}y \qquad (10)$$

where

A -area of region R ; K -length of border of region R.

Circularity will monotonously increase to infinite when region R tends to circle without affection of translation, rotation and scaling. In general, the connected component with less circularity corresponds to possible marking in binary image.

Self-organizing mapping [5] can identify a "natural break" in the data set. We use 1-D SOM consisting of an input layer and an output layer to classify values of circularity into three groups.

The number of nodes in input layer is the same as the dimension of the input vector, while the structure of the output layer is connected to each input node with some weights. Through competition, the index of the winning node is taken as the output of SOM. Hebbian learning rule is used to adjust the weight values of the winning node and its neighborhood nodes. Among these three nodes, node with less weight represents connected components that are more likely lane marking and, experimentally, its tenth is adopted as threshold T_2 to identify marking.

We define a new set of edges by

$$R_{markings} = \{R_i \in R : C_{R_i} > T_2\} \quad (11)$$

The possible lane marking are illustrated in Fig.5.

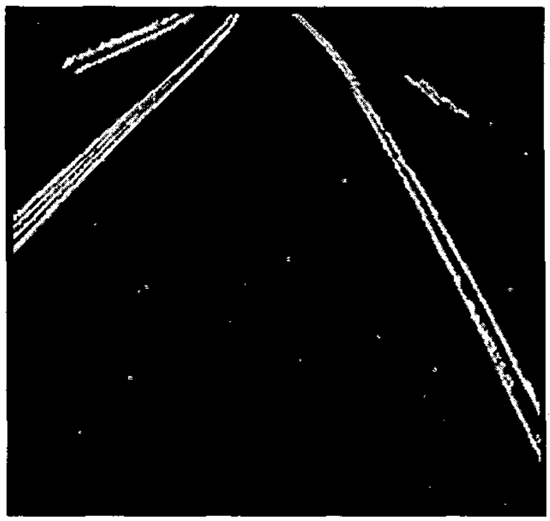


Fig. 5. Regions being possibly lane markings

V. CURVE FITTING

It is useful to fit a one-dimensional function through a set of data points. After determining region whose circularity is maximal, we use the method of deformable template to fit marking by minimum mean square error fitting.

$$j = s_1/(i - hz) + s_2(i - hz) + s_3 \quad (12)$$

where hz is the row in the image plane corresponding to the horizon under a flat earth assumption[6].

VI. EXPERIMENTAL RESULTS

We verify the suggested method by some challenging image and some results of detection are illustrated in Fig.6 (where (a) represents image with highlight in far field and shadows in near field, (b) represents image with yellow guard-rail similar to yellow marking, (c) represents image with shadows in far field, (d) represents image with cracks on the road surface, in all images, red lines show detected markings). It shows that the performance of our method is robust to lane marking in cluttered environment with shadows, highlight or pavement cracks.

VII. CONCLUSIONS

On the whole, the advantages of this algorithm are as follows: Firstly, it utilizes color information fully. Secondly, all thresholds are adaptively set without being predefined. Thirdly, the algorithm is efficient because it only requires an image to determine the marking. Lastly, it need no a prior knowledge. Furthermore, if some a prior knowledge is known, such as lane width, camera yaw angle and tilt angle, the other marking not detected can be derived. The experiment results show that the method based on circularity of connected components has outstanding robustness to lane marking detection and has a wide variety of applications in the areas of vehicle autonomous navigation and driver assistance system.

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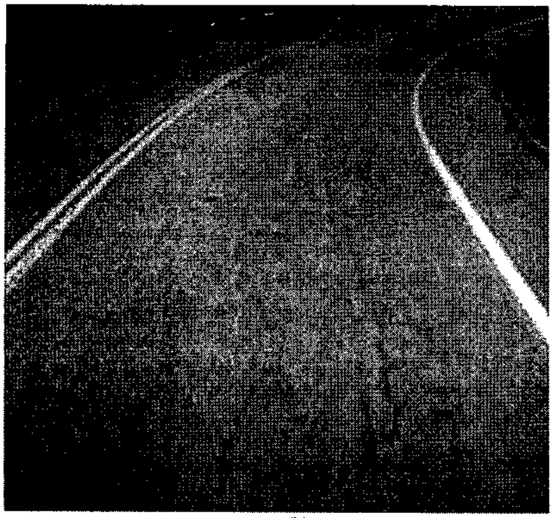
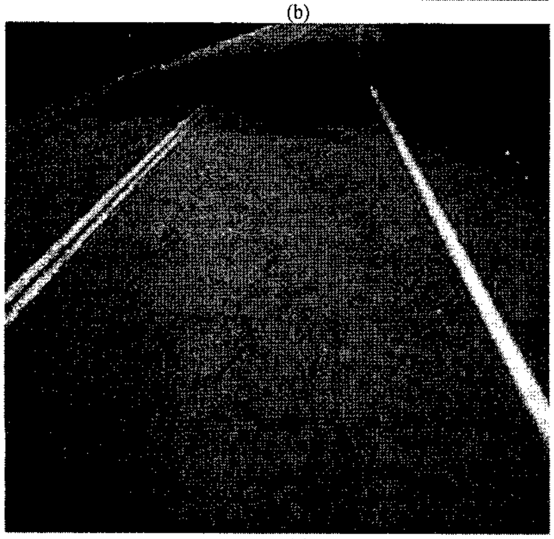
(a)



(b)

(d)



(c)

Fig. 6. Results of lane marking detection

REFERENCES

[1] M. Pietikainen et al., "Accurate color discrimination with classification based on feature distributions", International Conference on Pattern Recognition, 1996, pp.833-838.

[2] E. Littmann, H. Ritter, "Adaptive color segmentation: a comparison of neural and statistical methods", IEEE Trans. Neural Network, Vol.8, pp.175-185, Jan.1997.

[3] Y. Ohta, T. Kanade, T. Sakai, "Color information for region segmentation", Comput. Graphics Image Process, vol.13, pp. 222-241,1980.

[4] Haralick, M.Robert, and Linda G. Shapiro. "Computer and Robot Vision," Volume I. Addison-Wesley, 1992, pp. 28-48

[5] T. Kohonen, Self-Organizing Maps (third edition), Springer, Berlin, Germany, 2001.

[6] K. Kluge and S. Lakshmanan. "Lane boundary detection using deformable templates: Effects of image sub-sampling on detected lane edges," in Proc. 2nd Asian Conf. Computer Vision 1995, Singapore, 1995,pp.329-339.