A Robust Approach of Lane Detection based on Machine Vision

Bing Yu
School of Instrument Science and Engineering,
Southeast University
Nanjing, China
benyunj@hotmail.com

Weigong Zhang
School of Instrument Science and Engineering,
Southeast University
Nanjing, China
zhangwg@seu.edu.cn

***Abstract* -The lane detection is a key component of the intelligent transportation systems (ITS). We present a robust approach of lane detection based on machine vision. First, we present the lane model and region of interest (ROI) of the road image. Then, we propose the edge detection approach of the road image based on gray value grade. After that, we illustrate how to remove the interference points in the previous processed image; meanwhile, we describe how to gather the valid points. At last, we employ the coarse Hough transform to estimate the parameter values of the lanes. We present how to use Kalman filter to refine the estimation results. The field tests are carried on a local high-way and the experimental results show that the suggested approach is very reliable.**

Keywords-lane detection; Kalman filter; machine vision

I. INTRODUCTION

Lane detection is a key component of the intelligent transportation systems (ITS) applications. There have been many researches on lane detection, and various algorithms or approaches have been suggested in [1], [2], [3], [4], [5].

A common technique is based on detecting edges and fitting lines to these edges via the Hough transform [2], however, which is often sensitive to clutters from other vehicles and varying types of road signs. Techniques using tangent vectors have also been shown to be quite robust, but it fails when lane markings are not well defined [3]. Neural networks have also been employed to detect lanes and control vehicles [4],[5], but they only work on roads which are in their training set.

While these methods are all very effective at resolving these problems, they tend to be very specific to particular road conditions. The robust approach of lane detection is still an unsolved problem because in order to have a robust lane detector, the system must be applicable to all manners of road signs, road conditions, lighting changes, shadowing, and occlusion. In this paper, a robust lane detection approach is proposed. The Fast edge detection and high gray value pass filter are employed to gather the valid points of lanes, the coarse Hough transform is hired to estimate the parameter values of the lanes, and the Kalman filter is using to amend the parameter values.

This paper is organized into 7 sections. The status quo of the research is described in section 1. In section 2, a brief description of the lane model and the region of interest are introduced. In section 3, an approach of Fast edge detection based on gray grade is proposed. In section 4, the solution of how to remove interference points is presented. In section 5, the coarse Hough transform and Kalman amendment are proposed. In order to reduce the computational complexity of the Hough transform, the ROI [6] is resized to quarter of the original size or even smaller. Then the Kalman filter is employed to amend the results. In the last 2 section, the field test results and conclusions are given.

II. LANE MODEL AND REGION OF INTEREST(ROI)

The intelligent transportation systems applications make decisions depending on the detection of the lanes. Therefore, to detecting the lanes correctly is an important component.

978-0-7695-3728-3/09 $25.00 © 2009 IEEE
DOI 10.1109/CASE.2009.104

A typical model of the lanes is shown as Figure 1, the model of each lane can be considered as Equation (1) [7], where x_m represents the border between near and far fields. By choosing a proper x_m, the lanes can be treated as beeline in the near fields. And, the lane in the near fields can meet intelligent transportation systems applications' requirements.

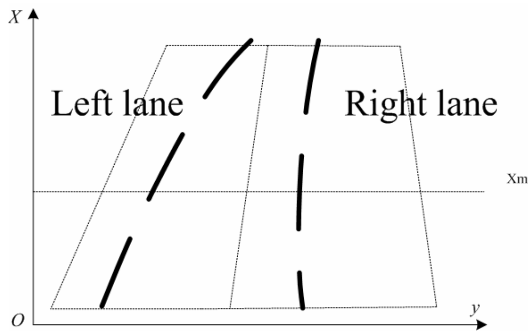

Figure 1 the lane model

$$\begin{cases} y = kx + d; x \geq x_m \\ y = ax^2 + bx + c; x < x_m \end{cases} \tag{1}$$

For an example, as shown in Figure 2, the upside is the region which contains the stuffs we may not pay attention to; while the underside includes the lane information we are interested in. By choosing a proper cutline, the image can be split as shown in Figure 2. We may only process the lanes in the underside of the image and we treat them as beelines. Furthermore, we can process the left lanes and right lanes respectively, thus, the underside of the image can be divided into ROI_1 and ROI_2.

Figure 2 the region of interest of the image

III. FAST EDGE DETECTION BASED ON GRAY GRADE

According to the marr theory, the contour is the primary element to recognize an image. Thus, the edge detection should be preformed before the reorganization. Unlike the usual sobel or candy operator, a fast edge detection based on gray grade is proposed. Consider the ROI_1 and ROI_2 in the Figure2; the lane marking contains the highest gray value in the region, while the gray value of the pavement is the lowest. As a result, the gray value changes suddenly at the lane edge. On the side ,as shown in Figure 1, The lanes extends in the direction of OX, so only OY direction of the ROI should be performed edge detection. The proposed solution in this paper is as following. Above all, a copy of the ROI is build, then gray grades calculation of OY direction is performed for each line of original ROI, if the gray grade is lower than a threshold, the corresponding pixel in the copied ROI will be set to zero. The Equation (2) is employed to get the gray grade, where the IMG is the ROI, and its width and height is m, n.

$$\text{ggrade} = \mathrm{I}MG(m,n) - IMG(m-10,n) \tag{2}$$

Figure 3 Image after fast edge detection

The Figure 3 illustrates the ROI_1 in Figure 2 after the fast edge detection processing. Duo to the road boundary, vehicles and arrow signs, there still has much interference in the figure. And the interference is should be tried to remove out.

IV. ITERATIVE HIGH GRAY VALUE PASS FILTER

For a ROI after the Fast edge detection processing, as shown in the Figure 3, the gray value of the lane marking is the highest. In order to extract the valid points of the lanes, the iterative high gray value pass filter is hired.

The iterative high gray value pass filter is illustrated as following. For an image after fast edge detection processing, the mean gray value of the nonzero points in the image is worked out firstly. Then, each nonzero point is compared with the mean gray value, if the gray value of the nonzero point is lower than mean gray value, the point gray value should be set to zero. Thus, a new image will be formed. Use the new image as input and repeat the same processing several times, most of the interferefering points will be removed.

V. COARSE HOUGH TRANSFORM AND KALMAN AMENDMENT

Based on the pre-works for lane detection discussed above, the follow-up process is how to estimate the *k*, *d* parameters in the Equation (1). Hough transform is an excellent solution to detect beeline, but it costs too many CPU's cycles. In order to improve the performance, the original ROI will be resized to quarter of the original size or even smaller. However, the noises in the ROI, such as text or sign mark with the same gray value as the lane, can not be removed completely; moreover, there is even no lane's information in the road image sometimes. The Hough transform will fail in these conditions. To overcome these problems, the Kalman filter is employed to refine the estimation results.

Based on the Kalman filter theory, the model of our system can be described as the Equation (3).

$$\begin{cases} X_k = X_{k-1} + W_{k-1} \\ Z_k = H_k X_k + V_k \end{cases} \tag{3}$$

With $X_k = \begin{bmatrix} k \\ d \end{bmatrix}_k$, $H_k = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_m \end{bmatrix}$, $Z_k = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}$,

$W_k \sim N(0, Q_k)$, $V_k \sim N(0, R_k)$.

Where m is the number of the valid points, and x, y are the coordinate-values of the valid points in the ROI. In case that the number of valid points is usually pretty high, the scalar measurement processing [8] is employed to simplify the processing. Using the theory of Partitioned Matrix, the H_k, Z_k and R can be partitioned as follows:

$$H_k = \begin{bmatrix} H_1 \\ \vdots \\ H_m \end{bmatrix}, \quad Z_k = \begin{bmatrix} Z_1 \\ \vdots \\ Z_m \end{bmatrix}, \quad R = \begin{bmatrix} R_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & R_m \end{bmatrix}.$$

Let $\hat{X}_1 = \hat{X}_{k,k-1}$ and $P_1 = P_{k,k-1}$, then we repeat the steps of equation (4), (5) and (6) from *i*=1 to *i*=*m*. If the parameter *m* is zero; we use the previous status of *X* and don't perform any calculation.

$$K_i = \frac{P_i \cdot H_i^T}{H_i P_i H_i^T + R_i} \tag{4}$$

$$\hat{X}_{i+1} = \hat{X}_i + K_i \left(Z_i - H_i \hat{X}_i \right) \tag{5}$$

$$P_{i+1} = \left(I - K_i \cdot H_i \right) \cdot P_i , \tag{6}$$

The prediction and status value of time k is P_{m+1} and $\hat{X}_{m+1}$ respectively.

VI. EXPERIMENTS RESULTS

Experiments based on this approach were performed on the Hu-Ning highways (a high way from Shanghai to Nanjing). These highways contained all of interferefering causes which have been mentioned above in this paper. Figure 4 shows the video sequences token from the experiments and experiments' results. The white line in the image is the line worked out by Coarse Hough transform, while the black line in the image is the line amended by Kalman filter**.** In this sequence, a vehicle in the road image causes the *k*, *d* value erring from the true value. However, the results amended by making use of the Kalman filter always track the lane accurately. Table 1 illustrates the k_h, d_h, k_k, d_k according to the video sequence shown in Figure 4, where k_h and d_h is the k, d parameters worked out by use of coarse Hough transform, and k_k, d_k is the k, d parameters amended by the Kalman filter.

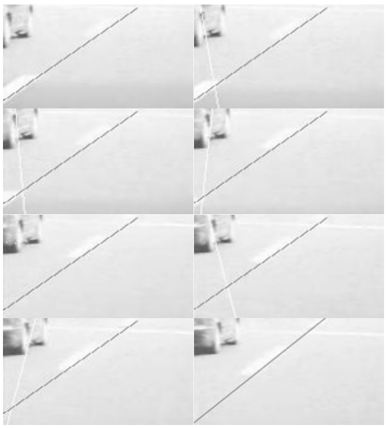

Figure 4 the image sequence of an experiment

Table 1 k, d parameters of each ROI in Figure 7

	k_h	d_h	k_k	d_k
1	-1.1504	113.9947	-1.1495	113.9946
2	0.1405	6.1234	-1.1103	113.9932
3	0.0699	10.1311	-1.0834	113.9939
4	0.0875	16.232	-1.0667	113.993
5	7.1154	-203.328	-1.0408	113.9935
6	0.2126	12.2986	-1.0350	113.9931
7	-0.2130	26.8636	-1.0295	113.9934
8	-1.0029	108.6236	-1.0032	108.6209

VII. CONCLUSIONS

It is very hard to detect the lane robustly; the varying road signs, clutters from other vehicles and varying road conditions often cause the results erring from the real status. In this paper, an approach of lane detection is presented and the field test results show its robustness to the complicated conditions. At first, the solution of how to choose the ROI is presented. Then, how to gather the valid points in the image is described. At last, the solution of the coarse Hough transform and Kalman amendment is illustrated. Future work will include the application of the lane departure approach in lane departure warning system and anti- collision warning system.

VIII. ACKNOWLEDGEMENT

The following organizations sponsored this project, Transportation Science Foundation of Jiangsu Province Communications Department (06C04), the Automotive Engineering Key Lab Open Foundation (QC200603), and Suzhou Science& Technology Development Foundation (SG0723).

References

[1] J. McDonald. *"Detecting and tracking road marking using the Hough transform."* Proc. of the Irish Machine Vision and Image Processing Conference, 2001.

[2]H. Furusho, R Shirato, M. Shimakage. *"A Lane Recognition Method Using the Tangent Vectors of White Lane Markers,"* 6th International Symposium on Advanced Vehicle Control, Sept. 9-13, 2002.

[3] Z. Kim, *"Realtime obstacle detection and tracking based on constrained Delaunay triangulation,"* in Proc. IEEE Intell. Transp. Syst. Conf., 2006,pp. 548–553.

[4] D. Pomerleau. Ralph: *"Rapidly adapting lateral position handler."* Proc. IEEE Symposium on Intelligent Vehicles, September 25-26, 1995.

[5]McCall, J. C. and M. M. Trivedi, *"An integrated, robust approach to lane marking detection and lane tracking,"* in Proc. IEEE Intelligent Vehicles Symp., Parma, Italy, June 14-17, 2004, pp. 533-537.

[6] A. López, C. Cañero, J. Serrat, J. Saludes, F. Lumbreras, and T. Graf, *"Detection of Lane Markings based on Ridgeness and RANSAC,"* IEEE Conference on Intelligent Transportation Systems, 2005, pp. 733-738.

[7] Cl´audio Rosito Jung, Christian Roberto Kelber,. *"A Lane Departure Warning System Using Lateral Offset with Uncalibrated Camera"*, IEEE Conference on Intelligent Transportation Systems.2005 Vol .pp.102-107

[8] Farrell, J.A. Givargis, T.D. Barth, M.J. *"Realtime differential carrier phase GPS-aided INS"*. IEEE Transactions on Control Systems Technology，2000，8 (4)：709—720.