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A novel curve lane detection based on Improved River Flow and RANSAC*

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***Abstract*—Accurate and robust lane detection, especially the curve lane detection, is the premise of Lane Departure Warning System (LDWS) and Forward Collision Warning System (FCWS). Lane detection on the structural roads under challenging scenarios such as the dashed lane markings and vehicle occlusion is a difficult task because of unreliable lane feature point. In this paper, a robust curve lane detection method based on Improved River Flow (IRF) and RANSAC method is proposed to detect curve lane under challenging conditions. The lane markings are grouped into a near vision field of straight line and a far vision field of curve line. The curve lanes are based on Hyperbola-pair model. To determine the coefficient of curvature, a novel method is proposed based on Improved River Flow method and RANSAC method. In the new method, Improved River Flow method is employed to search feature points in the far vision field guided by the results of detected straight lines in near vision field or the curve lines from last frame, which can connect dashed lane markings or obscured lane markings. So, it is robust on dashed lane markings and vehicle occlusion. Then, RANSAC is utilized to calculate the curvature, which can eliminate noisy feature points obtained from Improved River Flow. The experimental results show that the proposed method can robustly and accurately detect some challenging markings, such as the dashed lane markings and vehicle occlusion.**

I. INTRODUCTION

As a fundamental part of intelligent transportation systems, intelligent vehicles' obtaining and identification to the information of road plays a very important role in ITS, and lane detection is prerequisite for realizing lane departure warning and forward collision warning, it is also the key technologies for achieving intelligent vehicle vision aided. Lane detection in autonomous navigation systems and lane departure warning systems plays a crucial role, which can significantly reduce the occurrence of accidents due to the carelessness of the driver.

Lane detection comprises the straight lane detection and the curve lane detection. In most lane detection module, lane markings are processed as straight lines, the lane-curvature cannot be obtained and false alarms will be generated in a collision warning system. For example, without knowing the road curvature, the system cannot distinguish objects on the other lanes (e.g., the vehicle) from the objects on the own lane, and it may generate a false alarm. Therefore, we should achieve an accurate curve lane detection instead of straight lane detection，especially in the some challenging scenarios, such as the dashed lane markings and vehicle occlusion.

In this paper, we proposed a new approach of curve lane detection based on Improved River Flow and RANSAC. This method is mainly based hyperbola-pair model, the region of road on the front of own vehicle is divided two parts, one is the straight road area near the vision field, the other is the curve far from the vision field. In the premise of the straight lane markings has been detected, we search feature points by Improved River Flow on the curve lane of the far area, then, RANSAC is used to fit the curve lane by the searched feature points.

II. RELATED WORK

In recent years, many researchers carried on a great deal of research to lane detection. In general, vision-based lane detection can be categorized in two main classes. One is the feature-based method [1], [2], which can distinguish the feature points of lane markings from the points of non-lane markings by the feature of road image, such as the color, the width and the edge of lane. Kuo-Yu Chiu [1] proposed a method of color segmentation, it mainly uses threshold processing follow the color and fitting with a quadratic function. Kluge [2] proposed road detection method based on the ARCADE (Automated Road Curvature And Direction Estimation) algorithm. One problem of this method is the extraction of edge point locations and orientations from an image. These feature-based methods are simple, but it requires clear lane markings and large color contrast of lane, which are hard to meet under challenging scenarios, it is also easy to be influenced by changing in the surrounding environment.

The other is model-based [3], [4], [5], [6], [7]. The main work of this kind of methods determines a mathematical model according to the shape of road. Then the parameters of mathematical model can be solved by the feature points of lane markings from a road image. Thus the problem of lane detection turns into a problem of the parameters solution of the mathematical model. The difficulty in this kind of method is the extraction of feature points of lane markings from a road

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image, especially under some challenging conditions, such as the dashed lane markings and vehicle occlusion.

Wang Yue [3], [4] proposed a method for lane detection and tracking based on cubic B-Spline curve. The feature points of lane markings are extracted by Canny edge detection and Hough Transform in this method. Jung and Kelber [5], [6] used a linear-parabolic model for each lane boundary. The linear part is used to fit lane marking in the near vision field. The parabolic part of the model, which fits the far field, is then used to analyze the geometry of the road ahead (straight, right curve or left curve). In this method, a combination of the edge distribution function and a modified Hough Transform is used to extract the feature points of lane markings. In the work by Wang and Chen [7], a real-time lane detection algorithm based on a Hyperbola-Pair model is proposed. They think that some parameters of the model are same in the case of parallel lanes on the same road. This considerable insight is also used in our algorithm. A search strategy of mid-to-side is used to extract the feature points of lane markings. However, these model-based methods have not propose a robust and accurate method to extract the feature points of lane markings, especially in the far vision field, when using these methods to deal with the dashed lane markings or in the case of vehicle occlusion, an unpredictable result occurred.

A good lane detection algorithm should satisfy some challenging scenarios. However, the feature points on the curve lane markings are difficult to obtain in the far vision field particular under some challenging scenarios such as dashed lane markings and vehicle occlusion. In this paper, a robust method based on Improved River Flow and RANSAC is proposed which can work in some challenging conditions. The Improved River Flow can help accurately search feature points on the curve lane under challenging conditions.

The remainder of this paper is arranged as follows. Chapter 3 describes the hyperbola-pair model and introduced how to detect the straight lane on the near vision field. Improved River Flow is used to search feature points on curve lane and fitting with RANSAC in the chapter 4. Chapter 5 is the relevant experiment results and analysis. Finally, conclusion and future development are mentioned.

III. The Straight Lane Detection

A. Framework of Lane Detection

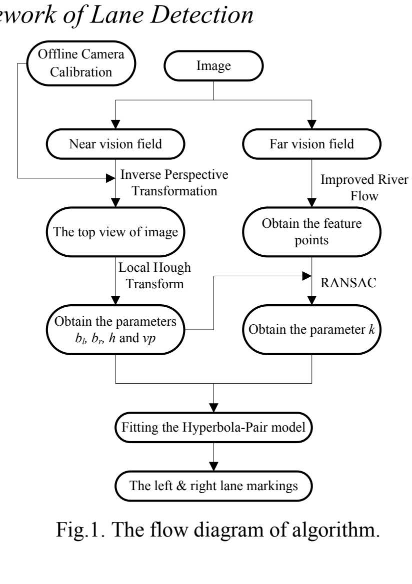


Fig.1. The flow diagram of algorithm.

Fig.1 shows the flow diagram of lane detection. The region of road on the front of vehicle is divided into two parts. One is the straight region in the near vision field; the other is the curve lane in the far field (Fig.2). A top view of road image is obtained by offline camera calibration and inverse perspective transformation in the near vision field. The parameters b_l、b_r、h and vp can be solved by Local Hough Transform based on linear model. In the far vision field, the coefficient of curvature can be solved by Improved River Flow and RANSAC. Finally, fitting the Hyperbola-Pair model by RANSAC and obtaining the left and right lane markings.

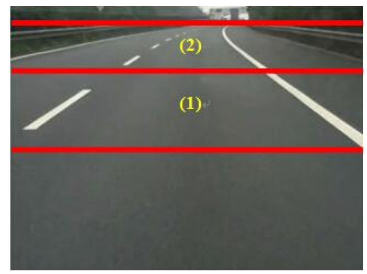


Fig.2. The division of lane region: The region (1) is the region of road in the near field. The region (2) is the region of road in the far field.

B. The Hyperbola-Pair Lane Model

According to the model proposed in [7], the hyperbola-pair road model corresponds with the road model of parallel parabolas in ground plane. For an arbitrary point of (u, v) on lane markings, we can express it using following equation,

$$\begin{cases} u_l = \dfrac{k}{v-h} + b_l \times (v-h) + vp \\ u_r = \dfrac{k}{v-h} + b_r \times (v-h) + vp \end{cases} \tag{1}$$

Where u_l or u_r are the left or right lane marking, k is the curvature of curve lane, b_l、b_r are the slopes of straight lane marking in the near field. h is the y-coordinate of the horizon, vp is the x-coordinate of the vanishing point. With the increasing of v, the value of $\frac{k}{v-h}$ can decrease. Therefore the hyperbola-pair road model can be approximated as follow equation in the near field.

$$\begin{cases} u_l = b_l \times (v-h) + vp \\ u_r = b_r \times (v-h) + vp \end{cases} \tag{2}$$

Compared equation (1) with equation (2), we can know that if we have detected the straight lane marking in the near field, the parameters b_l、b_r、h and vp can be solved. Thus, our algorithm of curve lane detection is divided two parts: estimating the parameters b_l、b_r、h and vp from the straight lane model in the near vision field, and determining the parameter k through the Improved River Flow and RANSAC.

C. Offline Camera Calibration

Camera Calibration can get 3D spatial information from the 2D images. It is a necessary step in the experiment and affects the subsequent experimental results. Calibration for vehicle-mounted camera is different from ordinary camera calibration, which requires calibration convenient, fast and easy onboard. In [8], a method of calibration for vehicle-mounted camera with a homemade 3D calibration plate is proposed, in which the special parameters of camera, such as tilt angle and yaw angle, can be calculated. The homemade 3D calibration plate includes two orthogonal Othello plates which consist of 4x4 and grid size of 150 mm × 150 mm. The results of camera calibration are shown in Fig.3.

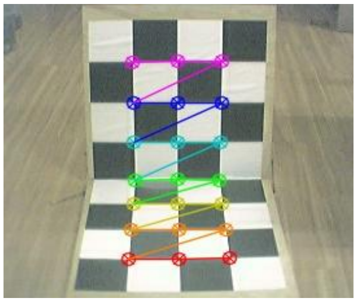
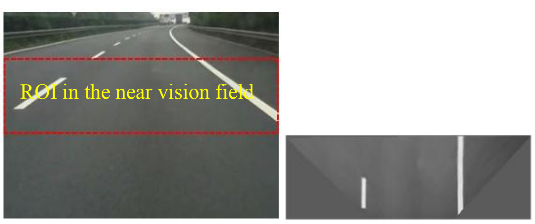


Fig.3. Offline Camera calibration by a 3D calibration board.

D. *The Local Hough Transform*

Hough Transform is a common method of line detection. In the method of Mohamed Aly [9], a Local Hough Transform method is used to detect and count how many lines there are in the top view road image, then using RANSAC algorithm to fit based on Bezier Splines. Refer to this method, in this paper, Local Hough Transform is used to detect the straight lane in the near vision field. Firstly, a region of interest in the near field is selected as a subimage(Fig.4(a)). Next, inverse perspective transformation is applied on the subimage to get the image of inverse perspective transformation. As is shown in Fig.4(b), the lane markings are parallel on the inverse perspective transformation.



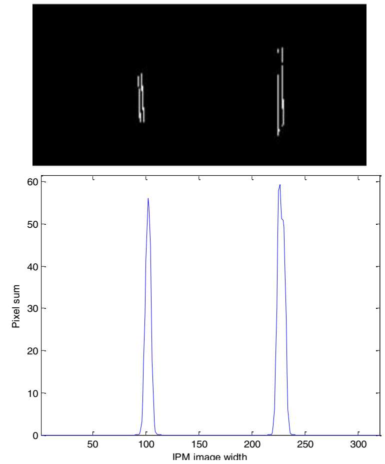
(a) (b)

Fig.4. Inverse perspective transformation of road image: (a) A region of interest. (b) The image of inverse perspective transformation.

The transformed subimage is then filtered by a two dimensional Gaussian kernel. The vertical direction is a smoothing Gaussian, whose σ_y is adjusted according to the required height of lane segment to be detected. The horizontal direction is a second-derivative of Gaussian, whose σ_x is adjusted according to the expected width of the lanes. After filtering, the Characteristics of lane is more obvious in the vertical direction. The result is shown in Fig.5(a).

$$\begin{cases} f_v(y) = exp\left(-\dfrac{1}{2\sigma_y^2}y^2\right) \\ f_u(x) = \dfrac{1}{\sigma_x^2}exp\left(-\dfrac{x^2}{2\sigma_x^2}\right)\left(1-\dfrac{x^2}{\sigma_x^2}\right) \end{cases} \tag{3}$$

SumPixel which is the sum of pixels of each column is counted on the subimage after filtering and binarization (shown in Fig.5(b)). If SumPixel>Th (Th is a threshold), there is a great probability of location of the lane markings for these pixels.



(a)

(b)

Fig.5. (a) The subimage after filtering and binarization. (b) The sum of pixels of each column.

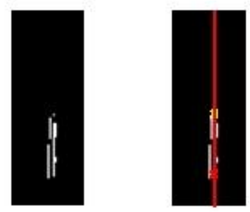


Fig.6. Line Detection with a Local Hough Transform.

According to the location where the lane marking may located on it, a Local Hough Transform, which needs less computing time and interference than the Global Hough Transform, is used to detect line around it(shown in Fig.6). Assuming the detected lane approximate a straight line, the model of polar coordinates can be expressed as follows:

$$\rho = xcos\theta + ysin\theta \tag{4}$$

(x, y) is the point of pixel on the image, ρ and θ are the parameters of polar coordinates. The result of straight lane detection in the near vision field is shown in Fig.7, the parameters b_l、b_r、h and vp also can be obtained.

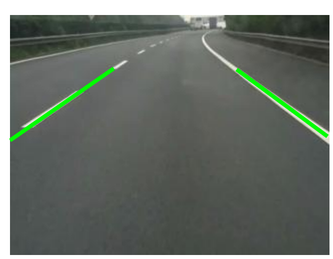


Fig.7. The result of straight lane detection in the near vision field.

IV. The Curve Lane Detection

The curve lanes are based on Hyperbola-pair model in which the coefficient of curvature is determined by our proposed method based on Improved River Flow method and RANSAC, while other parameters are determined by the straight lines. Improved River Flow method, which can better search feature points in the far vision field of curve lane under challenging scenarios, such as the dashed lane markings and vehicle occlusion, is utilized that the feature point is searched according to the straight line and curve line from last frame. In this section, the Improved River Flow and RANSAC are proposed to determine the coefficient of curvature k and fulfil the curve lane detection.

A. *The Improved River Flow*

In the far vision field, the feature points on the lane markings are difficult to obtain by edge detection or Hough Transform, especially under some challenging scenarios such as the dashed lane markings and vehicle occlusion. King Hann Lim [12] proposed a search method based on River Flow, which can search for feature points on curve lane in the far vision field. But the method is only applicable to continuous lane markings, the process of searching will be stopped and cannot search feature points in the far vision field of curve lane in the conditions of the dashed lane markings and vehicle occlusion, thus an unpredictable and even the false result occurred. To overcome this problem, in this paper, A Improved River Flow method, which can better search feature points in the far vision field of curve lane under challenging scenarios, such as the dashed lane markings and vehicle occlusion, is proposed to search feature points on the curve lane. The key of the Improved River Flow is that can connect dashed lane markings or obscured lane markings according to the results of detected straight lines in near vision field or curve lines from last frame. Thus, the process of searching cannot be stopped. The specific steps are as follows:

1) The pixel values of the straight line extended to far vision or the curve line detected by last frame image are set to 0.5 as shown in Fig.8.
2) The process of search starts from a start flowing point P (the top point on the detected straight lane markings in the near field).
3) Comparing the pixel values of points around this point with a mask 3×2 (Fig.9) and choose the feature point which has the maximum pixel value.
4) The searched point in 3) is used as the temporal start flowing point .
5) Repeating the steps of 3) and 4) until the end of searching.

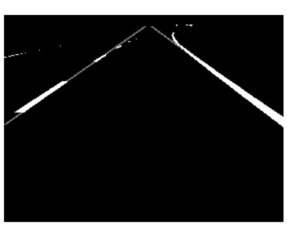


Fig.8. The direction straight line of searching feature points (gray line)

(x-1,y-1)	(x,y-1)	(x+1,y-1)
(x-1,y)	(x , y)	(x+1,y)

Fig.9. Mask 3×2 to obtain nearby pixels.

Fig.9 is the mask 3×2 to obtain nearby pixels. If the point $P_{x,y}$ is the start flowing point or last target point, $P_{x-1,y}$, $P_{x-1,y-1}$, $P_{x,y-1}$, $P_{x+1,y-1}$ and $P_{x+1,y}$ are the points around the point $P_{x,y}$, the next target point is obtain by the equation as follow,

$$P_{x,y} = max\begin{Bmatrix} P_{x-1,y}, P_{x-1,y-1}, P_{x,y-1}, \\ P_{x+1,y-1}, P_{x+1,y} \end{Bmatrix} \quad (5)$$

There are some constraints as follow:

1) Due to the application of lane detection, reversion of the point flow is prohibited. The lane flow is either moving forward or moving in the same row of current detected pixel.
2) An arbitrary point of higher pixel will be select if two or more same higher pixel values existed in the next flow.
3) The flowing process might halt if all the pixel values around the target point are zero or the target point is on the horizon.

The result of searching feature points on curve lane by Improved River Flow is shown in Fig.10. Fig.11(a) shows the result of searching feature points without using the direction straight line(red points), the process of search will be stopped in the dashed lane markings. Fig.11(b) shows he result of searching feature points with using the direction straight line(red points), it can finfish the process of search perfectly in the dashed marking.

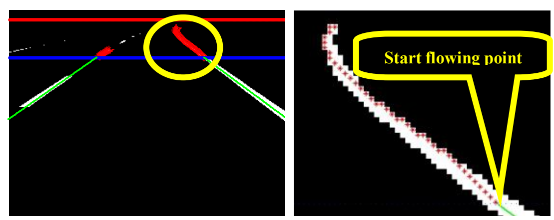
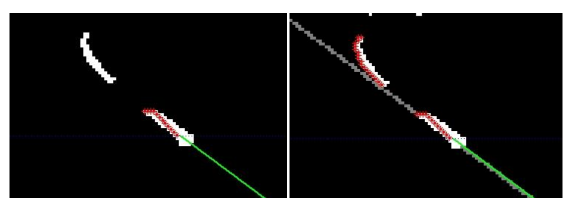


Fig.10. The result of searching feature points.



(a) (b)

Fig.11. (a) The result of searching feature points without using the direction straight line(red points). (b) The result of searching feature points with using the direction straight line(red points).

In the video sequences, we can search for feature points by using the curve line which is the result of hyperbola-pair model of last frame. Thus, the result will be more accurate than straight line.

B. *Fitting with RANSAC*

The RANSAC is the acronym of Random Sample Consensus that is used to calculate the parameters of the mathematical by a sample data set comprising a set of abnormal data. It was first proposed in 1981 by the Fischler and Bolles[13]. The RANSAC is better fitting curve line than the Least Square Method in the case of comprising abnormal data. The feature points obtained by IRF on left lane markings are $L = \{P_i | i = 1,2, \ldots, m\}$ and the feature points on right lane markings are $R = \{Q_i | i = 1,2, \ldots, n\}$, the hyperbola-pair is fitted with L and R by RANSAC. The fit processes are as follows:

1) For the set L and the model $u_l = \frac{k}{v-h} + b_l \times (v - h) + vp$ randomly select a feature point P_i from L, and get a corresponding parameter k_i, thus, a hyperbola-pair model is determined.

2) Calculate the distance between each feature point and the left hyperbola, if the distance less than a certain threshold t, the feature point is inner point and mark the number of inner points.

3) Repeat N times about the steps of 1) and 3), obtain some hyperbola-pair models and the number of corresponding inner points, the hyperbola-pair model which has most inner points is the better model and it's parameter k is k_l.

4) For the set R and the model $u_r = \frac{k}{v-h} + b_r \times (v - h) + vp$, we do like left and get the parameter k_r similarly.

5) Calculate respectively the number of inner points with the model of hyperbola-pair when the parameter k is k_l and k_r for all feature points, the hyperbola-pair model which has most inner points is the best model.

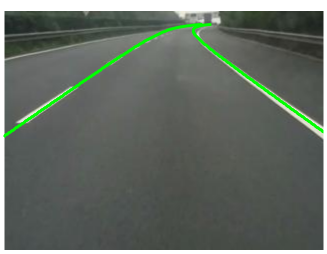


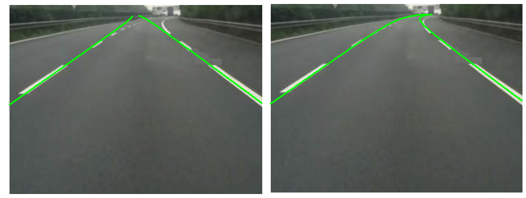
Fig.12. The result of curve lane detection

Of course, the times N and the threshold t are gotten by experiment. Thus, the all parameters of the hyperbola-pair model have been obtained. The result of curve lane detection is shown in Fig.12.

V. Experimental Results

The proposed method is tested on numerous conditions, including solid and dashed lane markings, straight and curve lanes, blurred lane markings, vehicle occlusion and road marks. The experimental video clips are downloaded at http://www.youtube.com/watch?v=qQHDvlsLu4c. The results of our experiment indicate the good performance of our algorithm for curve lane detection, especially under some challenging scenarios such as the dashed lane markings and vehicle occlusion.

Fig.13(a) shows the result of curve lane detection with the original River Flow and a false detected result occurred under dashed lane markings while the dashed lane markings are detected perfectly by IRF(Fig.13(b)).



(a) (b)

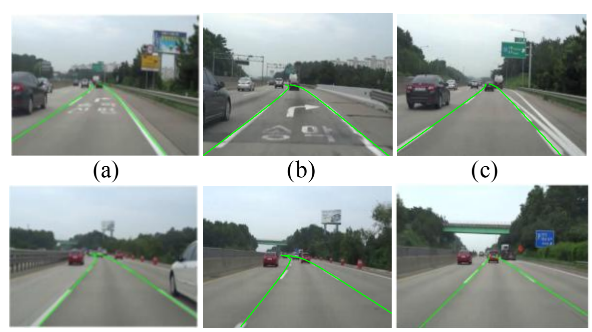
Fig.13. The result of curve lane detection. (a) The original River Flow. (b) The Improved River Flow.

Vehicle occlusion is a knotty problem in lane detection, especially when the color of vehicle is similar with lane markings. Some wrong points may be searched by IRF under this phenomenon without vehicle detection (shown in Fig.14(a)). So vehicle detection is important and necessary. The comparison results of lane detection with and without vehicle detection are shown in Fig.14. The results show that the lane detection performance can be promoted by vehicle detection.

(a) (b)

Fig.14. (a) The result of curve lane detection without vehicle detection (red points is the feature points). (b) The result of curve lane detection with vehicle detection.

Fig.15 shows some conditions of curve lane detection, (a)-(c) show the detection results of a combination of solid lane markings and dashed lane markings, part of lane markings are blurred and have middle road marks. Dashed lane markings are also detected accurately by the IRF and video information ((d)-(f)). (g)-(i) show the case of vehicle changing lanes. In the case of Vehicle occlusion ((j)-(l)), the lane markings are detected by vehicle detection and IRF. From the results, it is found that the proposed method can robustly and accurately detect both straight line and curve line under some challenge conditions.



(a) (b) (c)

(d) (e) (f)

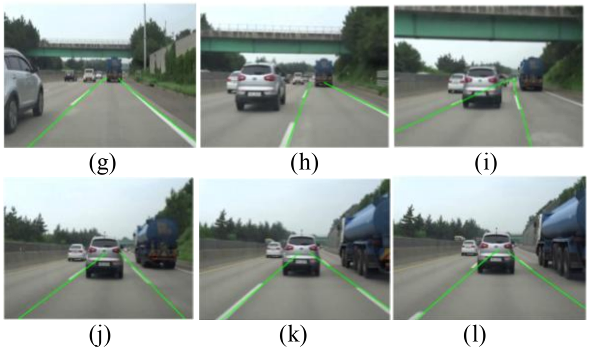


Fig.15. Some results of curve lane detection.

VI. CONCLUSION

In this study, we introduced a robust real-time lane-detection algorithm based on Improved River Flow and RANSAC for local roads and freeways of some challenging scenarios, such as the dashed lane markings and vehicle occlusion. A robust feature point search method by Improved River Flow has been proposed, which can better search feature points in the far vision field of curve lane under challenging scenarios. RANSAC can fits lane markings fast and accurately by these feature points.

The results of test indicate that our algorithm is robust, and meets the requirement of accuracy, it can provide good information of current lanes for driver, and is suitable for LDWS and FCWS. The reminder future works should focus on the lane-tracking methods and vehicle detection with tracking methods to promote the lane detection performance.

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