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A Multi-step Curved Lane Detection Algorithm Based on Hyperbola-Pair Model*

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***Abstract* - In this paper, we propose a multi-step algorithm based on a hyperbola-pair model for lane detection. We represent the lane markings on the road by a modified hyperbola-pair model, which contains two parts. The first one is a parallel straight line model, which is achieved by Hough transform. The second one is a hyperbola-pair line model, which is achieved by a searching strategy with the parameters got in the first stage as initial parameters. Experiment results show a robust performance in a noise condition, such as part of the lane markings are occupied by other vehicles in the lanes. The algorithm can provide accurate information of location and curvature of the lane markings in real-time.**

Index Terms – lane following, curve detection, hyperbola-pair model

Ⅰ. INTRODUCTION

With the development of transportation system, more and more vehicles are running on the highway every day. Traffic accidents attract more and more attention from research institutes and motor companies. Among all the accidents that caused by human faults, over 45% were caused by unattended lane departure and forward collision. If unattended lane departure and forward collision can be warning by a computer-based system, the accidents caused by these two reasons could be reduced dramatically. Such systems are called Lane Departure Warning System, or LDWS in short, and Forward Collision Warning System, or FCWS in short.

Among all the LDWSs and FCWSs studied now, the image-based processing technology is the most common way to achieve such an aim. In the image-based LDWSs and FCWSs, the road senses were captured by an on-board camera. The lane information and obstacles information were got by image analysis methods. In such image-based LDWSs and FCWSs, the most important thing is lane detection.

The lane detection algorithm of the image-based LDWSs and FCWSs should meet all the possible conditions that a normal human driver might meet while driving. It should meet all the illumination conditions, such as sunshiny, overcast or existing shadows which can be cast by trees, buildings, etc. It should be capable of processing the lane boundaries that can be marked: painted lines, whether solid or broken, blurred or occluded by other traffic participants. It should use the parallel constraint as a guidance to improve the detection of both sides of lane boundaries in a noise condition. It should handle the curved roads rather than assuming that the roads are straight. Handling a curved lane marking is very important, because it can avoid wrong forward collision warning when other vehicles driving in front but in another driveway of a sharp curved road. What is more, lane detection task must be finished in real-time, in order to give an enough action-time during real-emergence.

The remainder of this paper is organized as follows. In Section 2, we review some existing lane detection techniques. We are concentrated on those methods that use a curved lane representation model. In Section 3 we introduce the widely used hyperbola-pair model, and we modify this model into a two stage model, which contains a straight lane model and a curved lane model. The relationship between those two models is analyzed too. In Section 4 our approach for lane detection is presented, and Section 5 contains experimental

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results. Finally, conclusion is drawn in the last Section.

II. RELATED WORK

Many methods for curved lane detection have been proposed in the past years. Different approaches, such as watersheds, deformable models and stereo vision were used to tackle this problem.

Karl Kluge proposed a method [1] for estimating road curvature and orientation based on isolated edge points, without the need of grouping them. This system works if at most 50% of input edge points are noisy, which may not happen in practical situations.

An approach based on morphological filtering has been suggested in [2]. This technique used the morphological "watershed" transformation to locate the lane edges in the intensity gradient magnitude image. Although this technique has the advantage of not requiring any threshold for the gradient magnitudes, it has the disadvantage of not imposing any global constraints on the lane edge shapes.

Another class of lane detection methods [3] relies on top-view (birds eye) images computed form images acquired by the camera. These methods are reliable in obtaining lane orientation in world coordinates, but require online computation of the top-view images.

Deformable road models [4, 5] have been widely used for lane detection. These techniques attempt to determine mathematical models for road boundaries. In general, simpler models do not provide an accurate fit, but they are more robust with respect to image artifacts. On the other hand, more complex models are more flexible, but also more sensitive to noise.

Jung and Kelber used a linear-parabolic model [6, 7] for each lane boundary, and applied constraints to link both lane boundaries based on the expected geometry of the road. The linear part is used to fit lane borders 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.

Qiang Chen and Hong Wang proposed a lane detection algorithm [8] based on a hyperbola-pair lane boundary model. Instead of modeling each road boundary separately, they used a model to describe the road boundary as two parallel parabolas on ground plane. The Least Square method was adopted to estimate the model parameters.

Most of the methods mentioned above were used to fit the curve by finding out enough edge pixels of interest in ahead. In this paper, we propose a lane detection algorithm based on a modified hyperbola-pair model, which doesn't need to search for points of interest separately. We just think about the holistic relations among pixels.

III. HYPERBOLA-PAIR LANE BOUNDARY MODEL

We adopt the general road model proposed in [1], which assumes that each lane boundary forms a shape of hyperbola in the image plane, which can be expressed by the following formula given the road boundary point (u,v) in image plane,

$$u = \frac{k}{v-h} + b\left(v-h\right) + vp \qquad (1)$$

Where h is the y-coordinate of the horizon; k, b and vp are the parameters of the curve, which can be calculated form the shape of the lane on the ground and the calibration data of the camera.

According to the model proposed in [8], the hyperbola-pair road model corresponds with the road model of parallel parabolas in ground plane. The two lines formed by lane markings have the same parameters of k and vp. Assume that the two lane marking curves can be represented by

$$\begin{cases} u_l = \dfrac{k}{v-h} + b_l \times \left(v-h\right) + vp \\ u_r = \dfrac{k}{v-h} + b_r \times \left(v-h\right) + vp \end{cases} \qquad (2)$$

Then we analyze the physical meaning of parameters in equation (2). The initial parameters are assumed as follow: $h=100$, $vp=200$, $b_l=0.8$, $b_r=-0.8$, $k=0$, and we change the parameters respectively to see their physical meanings. As shown in Fig. 1(a)-(f), the initial lane boundaries were shown by dashed using magenta color and the lane boundaries whose some parameters having been changed were shown by solid line using black color. Parameter h changed to $h=50$ in Fig. 1(a), and it made the horizon become farther. Parameter vp changed to $vp=230$ in Fig. 1(b), and it made the lane boundaries produce horizontal displacement. Parameters b_l and b_r changed to $b_l=1.0$, $b_r=-0.6$ in Fig. 1(c), and they made the lane boundaries produce deflection. Parameters b_l and b_r changed to $b_l=1.0$, $b_r=-1.0$ in Fig. 1(d), and they made the lane boundaries become wider. Parameter k changed to $k=-200$ in Fig. 1(e), and it made the front lane have a left turn.

Parameter k changed to k=*400* in Fig. 1(f), and it made the front lane have a right turn.

So we can see that, parameter h controls the locality of horizon, parameter vp controls the horizontal displacement of road, parameters b_l and b_r control the width and deflection of road, and parameter k controls the turning of the lane.

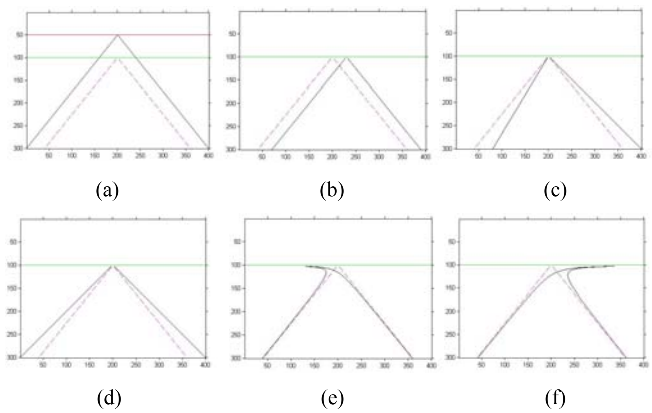


Fig.1. The physical meaning of parameters in hyperbola-pair model.

From Fig. 1(e)-(f) it can be seen that the value of $\dfrac{k}{v-h}$ which is the first term in the right side of formula will decreases as v increasing. The influence of this term will be much lower than the other terms' when the model is used to fit lane boundaries in the near vision field. Thus, in the near vision field the hyperbola-pair road model can be approximated by

$$\begin{cases} u_l = b_l \times (v-h) + vp \\ u_r = b_r \times (v-h) + vp \end{cases} \tag{3}$$

From the above modeling, it is easy to observe that the problem of detecting the curved road boundaries can be expressed as the problem of two parts: estimating the parameters b_l, b_r, h and vp from the straight line model in the near vision field, and determining the parameter k through the hyperbola-pair model. The viewing area of the lane is divided into two regions (near and far fields), as shown in Fig. 2(a).

But the assumption of changing straight line model for hyperbola-pair model in the near vision field is based on that the value of $\dfrac{k}{v-h}$ is much smaller than the other terms of (2). When the lane has a sharp curve, the value of k can reach to the grade of 10^3, while the maximum of v-h just can be the grade of 10^2. In this case, the term of $\dfrac{k}{v-h}$ has affected the lane in near field, we couldn't change the hyperbola-pair model to straight line model simply as above. For example, we change parameter k to k=*1000*, Fig. 2(b) shows that the straight line model which estimated from the near field of the curve produced a little horizontal displacement.

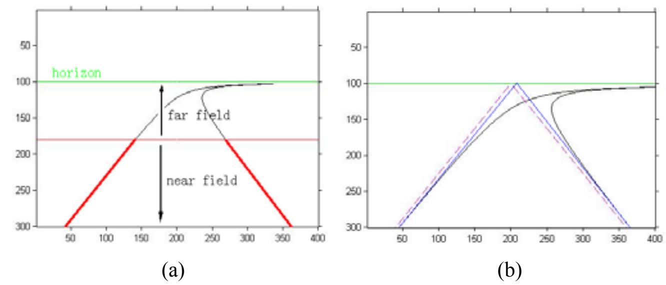


Fig.2. (a) The definition of the near and far fields.

(b) An instance of the lane with sharp curve.

To solve this problem, we transfer the influence of $\dfrac{k}{v-h}$ to parameter vp according to equation (2). By making parameter vp float in the field around its initial value estimated by straight line detection, while keeping the parameters b_l, b_r and h unchanged, we can obviously reduce the impact of initial straight line model on the finial detection of the curved road.

Ⅳ. LANE DETECTION

After applying the modified hyperbola-pair model, we divide our algorithm into two parts. The first one is estimating road parameters through straight line model, which is achieved by Hough transform. The second one is determining the parameter k through hyperbola-pair model, which is achieved by a searching strategy with the parameters got in the first stage as initial parameters. The structure of our algorithm is shown in Fig. 3.

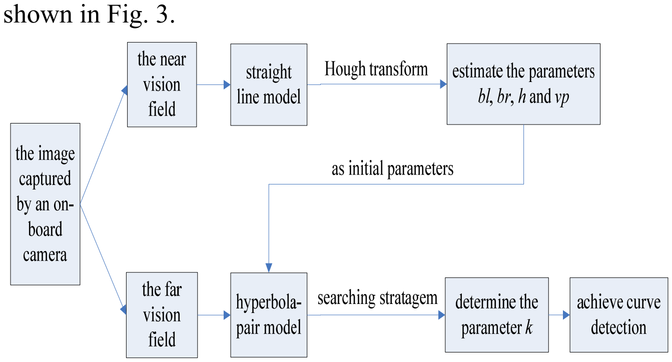


Fig.3. The structure of our algorithm.

A. Estimating Straight Road Parameters from the Near Vision Field

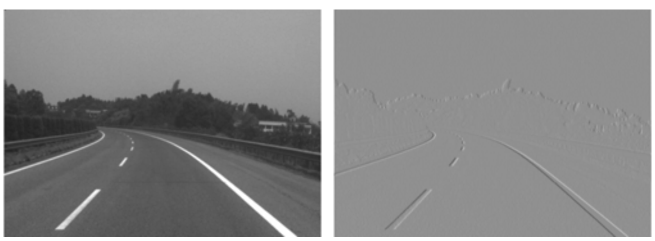
The road is assumed to have two parallel boundaries on the ground, and in the short horizontal band of image the road is approximately straight. As a result of the perspective projection, the road boundaries (either straight lane or curved lane) in the image should intersect at a shared vanishing point on the horizon. There are following processing stages in our algorithm:

1) Edge pixel extraction by Sobel edge detection.

Sobel edge detection is employed to obtain edge map. Because the lane in front of vehicle stretches lengthways, we just need to do Sobel edge detection for the vertical verge by

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

The result is shown in Fig. 4(b).



(a) (b)

Fig.4. Sobel edge detection. (a) An image captured by camera mounted on the vehicle. (b) The result after Sobel edge detection.

2) Define a threshold for later work.

In order to make the straight line detection easier and determine the parameter k later, here we define a threshold through a global self-adaptive iterative algorithm which is similar to clustering.

$$T = \frac{S_{\min} + S_{\max}}{2} \quad (5)$$

$$T_{next} = \frac{M_{S>T} + M_{S<T}}{2} \quad (6)$$

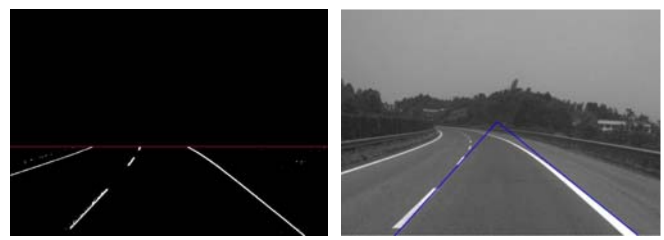
where S is the absolute value of pixel which has been computed by Sobel edge detection, S_{min} is the minimum of S, S_{max} represents the maximum, $M_{S>T}$ is the mean value of the pixels which satisfy the condition of $S>T$, $M_{S<T}$ is the mean value of the pixels which satisfy the condition of $S<T$, T is the initial threshold and T_{next} is the threshold after one step computing. Then we define

$$T = T_{next} \quad (7)$$

Do the process (6) and (7) iteratively until the formula $|T - T_{next}| < 1$ comes into existence. Here, T is the final threshold we need.

3) Straight lines detection by Hough transform.

The detected edge points are used to vote for possible lines in the space of line parameters. Here, for reducing the computational cost, we increase the threshold to *1.8T* and do Hough transform only for the points in the nether region of image (Fig. 5(a)). Here we just care about the boundaries of current driveway. By suitably confining the normalized accumulator spaces, line segments of current lane can be finally detected (Fig. 5(b)).



(a) (b)

Fig.5. (a) Edge points in the nether region of image whose values are greater than *1.8T*. (b) The line detected by Hough transform

4) Estimate parameters b_l, b_r, h and vp by the detected straight line.

The pair of straight lines in current lane has been detected in Hough space, and then it should be transformed into *u-v* coordinates.

According to the standard form of straight line

$$\begin{cases} v_l \cos\theta_l + u_l \sin\theta_l = \rho_l \\ v_r \cos\theta_r + u_r \sin\theta_r = \rho_r \end{cases} \quad (8)$$

The line can be formulated as

$$\begin{cases} u_l = -\cot\theta_l \cdot v_l + \dfrac{\rho_l}{\sin\theta_l} = b_l \cdot v_l + c_l \\ u_r = -\cot\theta_r \cdot v_r + \dfrac{\rho_r}{\sin\theta_r} = b_r \cdot v_r + c_r \end{cases} \quad (9)$$

Comparing to (3), we can see that

$$c_l = \frac{\rho_l}{\sin\theta_l} \qquad c_r = \frac{\rho_r}{\sin\theta_r}$$
$$b_l = -\cot\theta_l$$
$$b_r = -\cot\theta_r \tag{10}$$
$$h = \frac{c_l - c_r}{b_r - b_l}$$
$$vp = \frac{b_l h + c_l + b_r h + c_r}{2}$$

B. Determining the Parameter k through the Hyperbola-pair Model

After applying the straight line model for estimating parameters b_l, b_r, h and vp, we should determine the parameter k through hyperbola-pair model in order to describe the curvature for the real road.

1) Searching for parameter k.

From the hyperbola-pair model, we can see that: when the road is straight, k should be zero; if there is a left turn in the far field, k should be negative; and if a right turn, k should be positive. The road ahead is classified as:

$$\begin{cases} \text{straight}, & \text{if } k = 0 \\ \text{left turn}, & \text{if } k < 0 \\ \text{right turn}, & \text{if } k > 0 \end{cases} \tag{11}$$

The value of k may be so great with a sharp curve that we must choose a method to make k change from negative to positive within the range of possibilities. On the other way, the curvature of freeway is not large in most conditions. This means the value of k is small usually. Thus, it is best to make k change with a small step when its absolute value is not large and change with a large step when it is out of that scope.

Based on the description above, we choose k as:

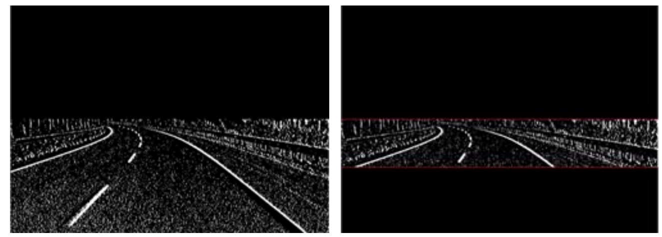
$$k = \tan\alpha \times 1000 \qquad (\alpha = -85 \sim 85\deg) \tag{12}$$

2) The searching region of parameter v.

After define the range of k, each value of k corresponds with a curve. We use the number of interest points which are on the corresponding curve to confirm parameter k. Here we use the threshold in (7) again. Because our algorithm can accommodate data consist of noises, the threshold is reduced to $0.5T$.

As shown in Fig. 6(a), it is clear that the number of valid points in near vision field is much larger than that in far field. If we define the searching region as $h\sim M$ on v-coordinate (M is the maximum of v), too many valid points in near field will be joined into computing the quantity of corresponding parameter k. Actually the main effect in searching method is caused by the points in far field. So decreasing the searching region of v can improve the result of lane detection dramatically.

Here we limit the search region of v to $h\sim h+100$ (Fig. 6 (b)).



(a) (b)

Fig.6. (a) Edge points in the region of $h\sim M$ on v-coordinate whose values are greater than 0.5T. (b) The searching region of parameter v.

3) The floating range of parameter vp.

As analyzed in Section 3, when the lane has a sharp curve, we can't change the hyperbola-pair model to straight line model simply. We should make parameter vp float in the range around its initial value, while keeping parameters b_l, b_r and h fixed.

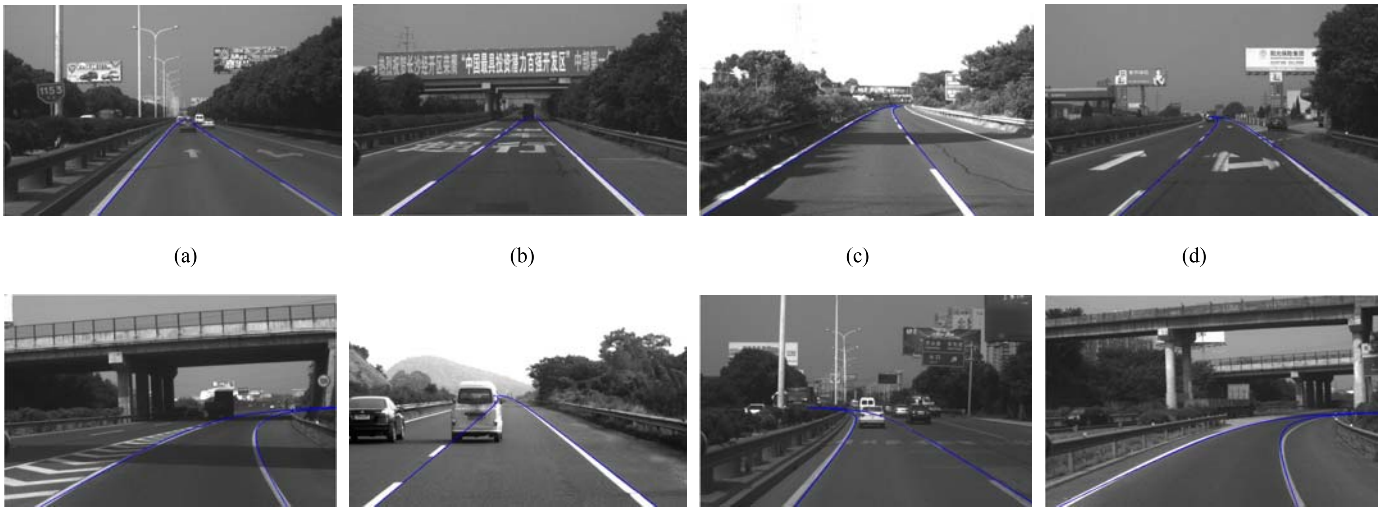
Because the parameter vp doesn't need to be changed intensely，we make parameter vp change from $vp-30$ to $vp+30$ by step 2. The result is shown in Fig. 7.

Fig.7. The result of lane detection by modified hyperbola-pair model.

V. EXPERIMENTAL RESULTS

We set up a database for experiment, which covers various conditions, including daytime and dusk, sunny and cloudy, straight and curve lanes, solid and dashed markings, etc. The results of our test indicate the performance of our algorithm for lane detection.

Fig. 8(a)-(b) show the detection results for lanes which are approximately straight. Fig. 8(c)-(e) show the curved road detections. Fig. 8(f) shows a detection result with partially occupied boundary. Among them, (a)-(d) have solid and dashed markings; (b) and (d) also have broken or blurred parts, while arrows and signs existing on the road; (c) and (e) own shadows; (a) and (b) exist other vehicles on the current lane. It can be seen that our algorithm achieves very good localization of the lane markings.



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig.8. Some results of lane detection

Ⅵ. CONCLUSION

In this paper, we propose a multi-step algorithm based on a modified hyperbola-pair model for lane detection, which doesn't need to search for points of interest separately and fit the model by the points. By estimating the requisite parameters separately from straight line model and hyperbola-pair model, our algorithm shows a robust performance in a noise condition. The results of our experiment indicate that the algorithm meets the requirement of accuracy, provides information for locating and orienting the current lane, and is suitable for LDWS and FCWS.

By the way our algorithm still has some places unsatisfied by now. As shown in Fig. 8 (g)-(h), a sharp curve combined with undulate road or an interference caused by too many vehicles in the far field creates a situation that the estimated locations are in error near the horizon. In our experiment we also tried to use parameter *h* floating for fitting undulate road and make the result more accurate by brightness-based grading，but we didn't get satisfying results. At present, the algorithm is in the phase of processing single frame. Future work will include processing the frame sequences and implementing the algorithm on an embedded image processing system.

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