A VISION BASED ROBUST LANE DETECTION AND TRACKING ALGORITHM

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ABSTRACT

Lane Detection is a difficult problem because of the varying road conditions that one can encounter while driving. In this paper we propose a method for lane detection using steerable filters. Steerable filters provide robustness to lighting changes and shadows and perform well in picking out both circular reflector road markings as well as painted line road markings. The filter results are then processed to eliminate outliers based on the expected road geometry and used to update a road and vehicular model along with data taken internally from the vehicle. Results are shown for a 6000-frame image sequence that include varying lane markings, lighting conditions, showing, and occlusion by other vehicles. The overall structure of lane detection is the same as the conventional method using monocular vision: EDF (Edge Distribution Function)-based initialization, sub-ROI (Region of Interest) for left/right and distance-based layers, steerable filter-based feature extraction, and model fitting in each sub-ROI.

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1. INTRODUCTION

Lane detection is a well-researched area of computer vision with applications in autonomous vehicles and driver support systems. This is in part because, despite the perceived simplicity of finding white markings on a dark road, it can be very difficult to determine lane markings on various types of road. These difficulties arise from shadows, occlusion by other Vehicles, changes in the road surfaces itself, and differing types of lane markings.

A lane detection system must be able to pick out all manner of markings from cluttered roadways and filter them to produce a reliable estimate of the vehicle position and trajectory relative to the lane as well as the parameters of the lane itself such as its curvature and width.

Figure.1. An example of a highway road, lane markings cluttered by shadows and other vehicles.

Figure 1 shows examples of the varying highway markings that must be looked at when creating a lane detector.

The desired properties of lane detection techniques include:

1) Quality of lane detection should not be affected by shadows, which can be cast by trees, buildings, etc.

2) It should be able to handle the curved roads instead of assuming that the roads are straight.

3) It could assume the parallelism of both sides of the lane markings to improve the detection in the existence of noises in the images.

4) It should provide an explicit reliable measurement of the obtained result that we could know whether to abandon the method.

A good lane detection algorithm should satisfy all the properties mentioned above. So in this paper, we will introduce a model-based lane detection algorithm which is robust and satisfies all the above properties.

One of the major disturbances of lane detection is occlusion by the preceding vehicle. Therefore, position information of the preceding vehicle makes the lane detection algorithm simpler and more robust. Otherwise, the lane detection algorithm is supposed to be complicated because it should handle various cases including the preceding vehicle occlude lane markings.

1.1 ADAPTIVE ROI-BASED LANE DETECTION

The lane detection proposed by this paper is fundamentally based on the monocular vision-based lane detection published by [1] and [2]. The forward scene is divided into three layers according to distance and divided into LHS (Left Hand Side) and RHS (Right Hand Side) again. In these six regions, lane features are searched locally. Lane feature pixels are detected by steerable filter and are approximated into a line or a parabola. The orientation of steerable filter is initialized by peak detection of the EDF (Edge Distribution Function), and then established according to lane feature state predicted by temporal tracking. Regions of the lowest layer are fixed but regions of the second and third layer are set dynamically. The conventional lane detection system works well when there is no obstacle in the vicinity. Recently, as the HDRC (High Dynamic Range CMOS) camera is adopted, traditional problems such as driving against the sun and tunnels are overcome [3]. However, if the preceding vehicle occludes lane markings or a vehicle in the adjacent lane approaches, lane features become lost or too small. As a result, edges of the obstacle start to disturb lane detection. To overcome such problems, ROI Establishment based on precise trajectory prediction using vehicle motion sensors and lane feature verification-based outlier rejection are incorporated[1].Assuming that disturbance of neighbouring vehicles occurs because the system has no knowledge about free space, this paper proposes that simple confinement of ROI to free space can efficiently prevent the disturbance of neighbouring vehicles.

2. CONVENTIONAL SYSTEM: MONOCULAR VISION-BASED LANE DETECTION

2.1 THREE LAYERED ROI STRUCTURE

Lane markings have different shapes according to the road shape as shown in Fig. 2. If the road is straight as in Fig. 2(a), all lane markings, both near and far, can be approximated as a straight line. If the road is curved as in Fig. 2(b), lane markings at near and far distances should be approximated as a straight line and a curve respectively.

(a) Straight road (b) Curved road

Figure.2. Lane shape depends on road shape.

ROI should be established such that the searching area is minimized but still contains the lane features. Desirable ROI is expected to include lane features and exclude image portion belonging to other objects. Considering the fact that the lane becomes smaller as distance increases, the searching area is divided into three layers whose size decrease gradually, and then divided into LHS and RHS. Consequently, six sub-ROIs are established. The height of available searching area changes according to camera configuration and the height of each layer is defined as the ratio to the height of available searching area. Sub-ROI I and IV near to the subjective vehicle is established fixedly and sub-ROIs of second and third layer are established using the lane detection result of their lower layer [2]. In other words, the detected lane of sub-ROI I determines the location of sub-ROI II and the detected lane of sub-ROI II determine the location of sub-ROI III again.

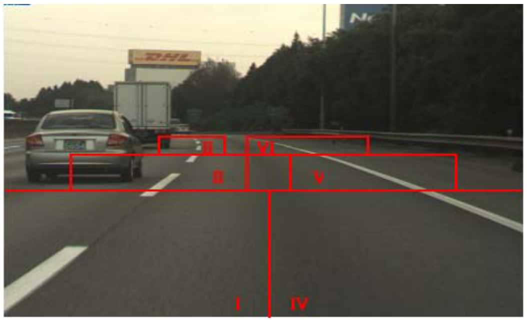


Figure.3. Three layered ROI structure.

2.2 STEERABLE FILTERING

The input image stream usually contains lanes in various directions which are redundant to the problem of autonomous drive. Therefore it is required to apply oriented edge detectors to different parts of the image such that the unwanted lanes are suppressed. One approach to do so is to apply many versions of an edge detector each of which differing from others in the angle, to different parts of the image. This approach obviously consumes huge amount of extra logic and is not reasonable to implement, although is quite fast. A more efficient approach is proposed by [4] in which required filters of arbitrary orientation can be expressed as a linear combination of a set of basis filters. One then only needs to know how many filters are required and what interpolation function satisfies the requirements. This class of oriented filters is referred to as Steerable Filters.

The steerable filter is defined using the 2D (two dimensional) Gaussian function of (1). If the lane marking is regarded as a line having width, then second derivative is used [1]. If the inner edge of lane marking is regarded as lane feature, then first derivative is used [2, 5]. In our research, first derivatives defined as in (2) and (3) are used. Equation (2) is the derivative of (1) in x-axis direction (θ =0°) and (3) is the derivative of (1) in y-axis direction (θ=90°). It is noteworthy that the

Equations from (1) to (3) define 2D masks.

$$G(x,y) = e^{-(x^2+y^2)} \qquad (1)$$

The first x derivative of a Gaussian $G_1^{0^0}$ is

$$G_1^{0^0} = \frac{\partial}{\partial x} e^{-(x^2+y^2)} = -2xe^{-(x^2+y^2)} \qquad (2)$$

The same function, rotated 90^0, is

$$G_1^{90^0} = \frac{\partial}{\partial y} e^{-(x^2+y^2)} = -2ye^{-(x^2+y^2)} \qquad (3)$$

A G_1 filter at any arbitrary orientation θ can be synthesized by taking a linear combination of $G_1^{0^0}$ and $G_1^{90^0}$:

$$G_1^{\theta} = \cos(\theta) G_1^{0^0} + \sin(\theta) G_1^{90^0} \qquad (4)$$

Since $G_1^{0^0}$ and $G_1^{90^0}$ span the set of G_1^{θ} filters, we call them basis filter for G_1^{θ} .The cos (θ) and sin (θ) terms are the corresponding interpolation functions for those basis filters.

Because convolution is a linear operation, we can synthesize an image filtered at an arbitrary orientation by taking linear combination of the images filtered with $G_1^{0^0}$ and $G_1^{90^0}$ Letting * represent convolution, if

$$R_1^{0^0} = G_1^{0^0} * I \qquad (5)$$

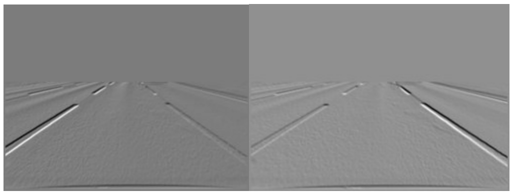
$$R_1^{90^0} = G_1^{90^0} * I \qquad (6)$$

then

$$R_1^{\theta} = \cos(\theta) R_1^{0^0} + \sin(\theta) R_1^{90^0} \qquad (7)$$

The filter defined in (4) outputs strong response to edges perpendicular to the specific direction θ and outputs weaker response as the angular difference increases. Therefore, because the possibility that edges of shadow and stain have the same orientation as lane feature is very low, steerable filter tuned using *a priori* known lane feature direction can selectively detect lane feature, more exactly lane feature pixels. Fig. 4(a) is an input image and (b) and (c) are the outputs of steerable filter tuned to -45° and 45° respectively.

(a) Input image



(b) Output (θ =-45°) (c) Output (θ =45°)

Figure.4. Lane feature pixels detected by tuned steerable filter.

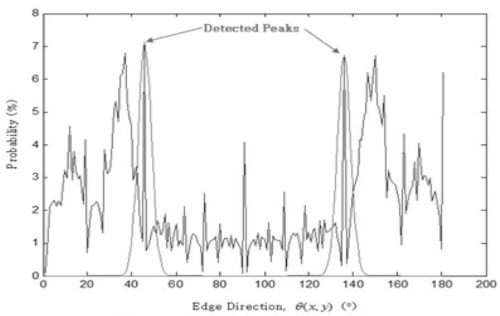
2.3 EDGE DISTRIBUTION FUNCTION

EDF is used to initialize the orientation parameter of steerable filter. EDF is the histogram of edge pixel direction with respect to angle [2, 6]. Equation (8) defines the gradient of pixel (*x*, *y*). D_x Denotes the intensity variation with respect to x-axis and D_y denotes the intensity variation with respect to y-axis. Gradient is approximated by Sobel operator. With D_x and D_y edge direction at pixel (*x*, *y*) is defined as in (9). After edge direction of all pixels in ROI is calculated using (9), EDF can be constructed by accumulating pixel occurrence with respect to edge direction. Fig. 5(a) shows the Sobel operator result of Fig. 4(a) and Fig. 5(b) is the constructed EDF

$$\nabla I(x, y) = \left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right)^T \approx (D_x, D_y)^T \qquad (8)$$

$$\theta(x, y) = \tan^{-1}\left(\frac{D_y}{D_x}\right) \qquad (9)$$

(a) Gradient image by Sobel operator



(b) EDF and detected peaks

Figure.5. EDF construction and peak detection.

After dividing EDF into two regions with respect to 90°, the maximum peak of each region is detected. The left portion is corresponding to sub-ROII of Fig. 2 and the right portion is corresponding to sub-ROI IV. As mentioned before, lane feature in the lowest layer can be approximated by a line and the angle of detected peak represents the direction of lane feature of each sub-ROI. Therefore, the angle corresponding to the detected peak is used for the initialization of orientation parameter of the steerable filter.

3. LANE DETECTION SYSTEM

Lane feature detection consists of steerable filtering, Hough transformation, inner edge point detection, and model fitting. Figure 6 presents the procedure of initial lane feature detection. A steerable filter tuned to an a priori known lane direction and binarization detects lane feature pixels. Using the lane feature pixels, a Hough transform finds the lane feature. The second column of Figure 6 shows the Hough transform results; the horizontal and vertical axes represent parameters of the linear lane model. In the case of the lowest layer, the orientation of the steerable filter is set using the EDF and in the case of the other layers, it is set by lane feature state tracking, which is explained below. The initial lane feature found using the Hough transform is a linear approximation of pixels showing strong the steerable

filter tuned to a specific direction using the voting method. By searching the edge point from the lane
feature to the image centre, the inner edge points are detected.

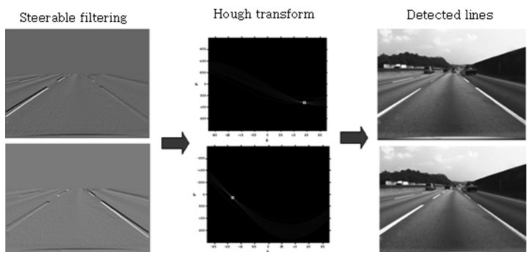


Figure.6. Initial lane feature detection.

The overall system that we have implemented is diagrammed in Figure 6. The video input to the system are taken from a forward looking rectilinear camera for our test results, but can be taken from any number of cameras on our test bed vehicle. For more information on this test bed, please refer to [7]. Information about the vehicles state including wheel velocities and steering angle are acquired from the car via the internal CAN bus. These inputs are then fed into the tracking system to determine the state of the vehicle and road. The lane angles in the image coordinates are then feed back into the filtering algorithm in order to tune the filters for specific lanes.

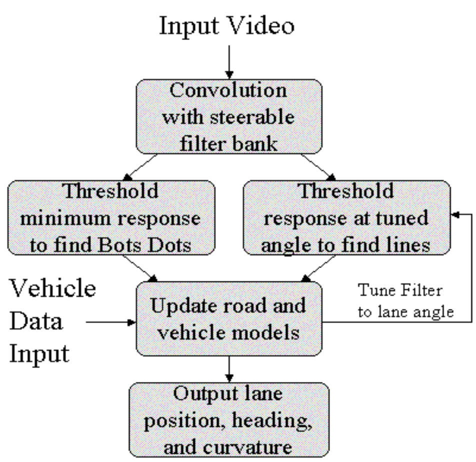


Figure.7. The Lane Tracking System Flow Chart.

3.1 ROAD MODELING

The road model used in our system is similar in form to that used in [8]. The state variable include the vehicle offset from the center of the lane, the vehicle heading with respect to the lane, the rate of change of the lane heading, the steering angle of the vehicle, and the velocity of the vehicle. Currently lane curvature is estimated using the steering angle and the rate of change of the lane heading and is only estimated at the vehicles location. The camera pitch and lane width are assumed constant in this implementation. The vehicle state is updated in time each frame as well as updated from the measurements via a Kalman filter, which is described at the end of the next section.

3.2 LANE TRACKING

In order to perform robust tracking, some more post processing on the filter results is performed. First, only the filter candidates within the vicinity of the lanes are used in updating the lanes. This removes outliers from other vehicles and extraneous road markings. Secondly, for each lane, the first and second moments of the point candidates are computed. Straight lane markings should be aligned to that there is a high variance in the lane heading direction and a low variance in the other direction. Outliers are then removed based on these statistics. Because the algorithm uses a local search about the lanes for candidates, it requires initialization. In testing, it was sufficient to initialize the lane tracker position and trajectory to zero (corresponding to the center of the lane). These computed headings and positions in image space are then transformed into real-world coordinates via an inverse perspective calculation. The state variables are then updated using these measurements as well as measurements of steering angle and wheel velocity provided by the vehicles CAN bus. These measurements are then feed into a discrete time Kalman filter for the road and vehicle state as described in section 3.1. The system and measurement equations as well as the Kalman update equations at time k are shown below.

$$x_{k+1|k} = Ax_{k|k} + Bu_k \tag{10}$$

$$y_k = Cx_k \tag{11}$$

$$P_{k+1|k} = AP_k A^T + Q \tag{12}$$

$$P^{-1}{}_{k+1|k+1} = C^T R^{-1} C + P^{-1}{}_{k+1|k} \tag{13}$$

$$K = P_{k+1|k+1} C^T R^{-1} \tag{14}$$

$$x_{k+1|k+1} = x_{k+1|k} + K(y_{k+1} - Cx_{k+1|k}) \qquad (15)$$

4. EXPERIMENTAL RESULTS

We tested our lane detection/following algorithm for different video sequences containing several conditions that may degrade the accuracy of the proposed algorithm, such as varying illumination conditions, presence of shadows and weak painting of the lane markers. All video sequences in this work were obtained at 60 frames per second, with a resolution of 752 × 480 pixels.

A. Result in single frame

Fig. 8 shows the result of the proposed algorithm in single frame.

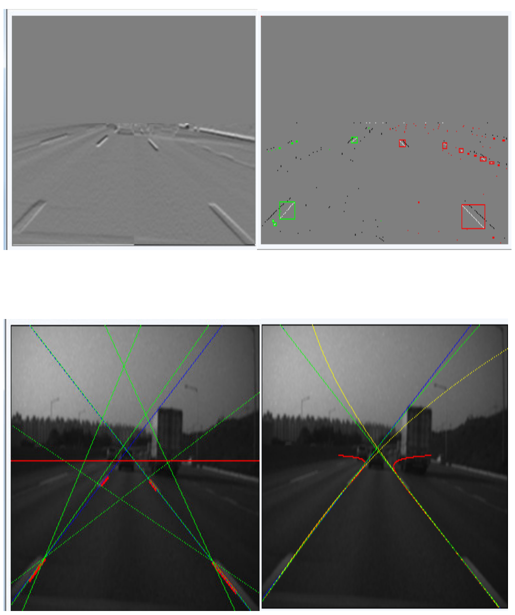


Figure.8. Lane Detection Results in single frame

B. Result in consecutive frames

We tested our algorithm in consecutive frames in video file. Some frames are shown in Fig.9.

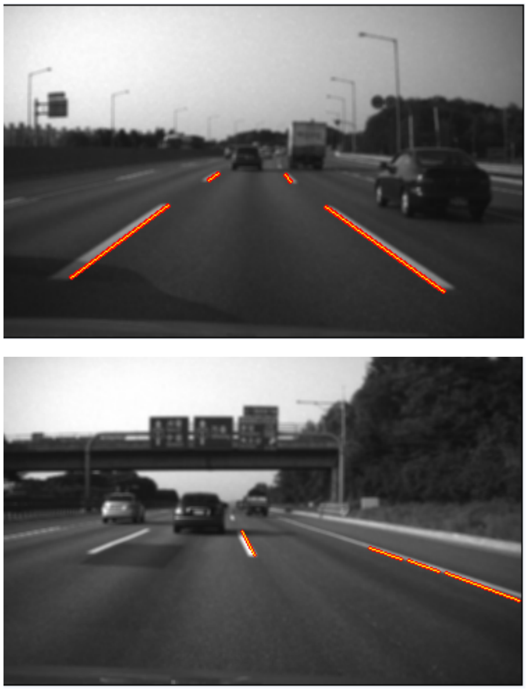


Figure 9. Result in consecutive frames

5 CONCLUSION

We have developed a road detection algorithm on the marked road which can be used for Lane Departure Warning System or other auxiliary driving system. Lane detection is often complicated by varying road markings, clutter from other vehicles and complex shadows, lighting changes from overpasses, occlusion from vehicles, and varying road conditions. In this paper we have presented a solution to the lane detection problem that shows robustness to these conditions. We have shown that using a steerable filter bank provides robustness to lighting changes, road marking variation, and shadowing.

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