Computer Vision-Based Multiple-Lane Detection on Straight road and in a Curve

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Abstract— **A vision system was designed to detect multiple lanes on structured highway using an "estimate and detect" scheme. It detected the lane in which the vehicle was driving (the central lane) and estimated the possible position of two adjacent lanes. Then the detection was made based on these estimations. The vehicle was first recognized if it was driving on a straight road or in a curve using its GPS position and the OpenStreetMap digital map. The two cases were processed differently. For straight road, the central lane was detected in the original image using Hough transformation and a simplified perspective transformation was designed to make estimations. In the case of curve path, a complete perspective transformation was performed and the central lane was detected by scanning at each row in the top view image. The system was able to detected lane marks that were not distinct or even obstructed by other vehicles.**

Keywords— **multiple-lane detection; image processing; curve detection; perspective transformation; computer vision**

I. Introduction

Lane detection attracted extensive research interest in recent decades and many works had been reported to be able to detect the lane in which the vehicle was driving (the central lane) for lane following purpose [1-5]. However, few of them dealt with the multiple-lane detection problems. Beyond providing the vehicle's position in the lane, multiple-lane detection is also useful in other applications, including providing lane-level accuracy for GPS-based navigation and detecting vehicles in multiple lanes.

In comparison to the central lane, the adjacent lanes are difficult to detect because of the following reasons: (1) they are not as distinct as the central lane; (2) they are likely be partly obstructed by other vehicles; (3) shadows or other noise in the image interferes the detection.

This paper presents a vision system to fulfil the task of multiple lanes detection on structured highway. The system detected the central lane first. Under the assumption that lane marks were in parallel with each other with the same interval and that the road was flat, the position of the adjacent lanes was estimated in top view by offsetting the central lane marks. Then the adjacent lanes could be detected based on the estimations with high confidence.

II. Materials and Methods

A. Hardware

The system worked as a part of a stereo vision system for vehicle detection in multiple-lane scenario but no stereo vision processing was involved in the lane detection. Images from the left camera of a stereo vision pair STH-MDCS3-VARX (Videre Design LLC.) was processed by a laptop equipped with an Intel Core 2 Duo processor U9400. The data processing program was developed using Visual C++ 2003 (Microsoft Co., Redmond, WA, USA) and SVS API (Videre Design LLC.). The camera uploaded images (resolution of 640×480, monochrome) to the computer via IEEE-1394 firewire at a rate of 15 fps (frames per second). The camera had been calibrated offline using the program provided by the manufacturer and the collinearity in the real world was recovered in the rectified images. The calibration also output the cameras' parameter including the imager size and the centre position of the image that was used in the following processing.

B. Data processing algorithm

The data processing algorithm for multiple-lane detection was following a so-called "estimate and detect" scheme. Though it was relatively simple to detect the central lane, the system employed different procedures to do this task depending on if the vehicle was driving on straight road or in a curve.

The road condition was recognized using the vehicle's GPS position and the "OpenStreetMap" digital maps. Roads in the "OpenStreetMap" are represented using sets of nodes whose longitude and latitude were all known and the curvature of the road could be calculated.

1) The case of straight road:

The flow chart of the case of straight road was shown in Fig.1; a sample image was given in Fig. 2 (a). In this case, the central lane was detected using Hough transformation in the original image directly and a simplified perspective transformation was applied to the detection result for estimating the adjacent lanes.

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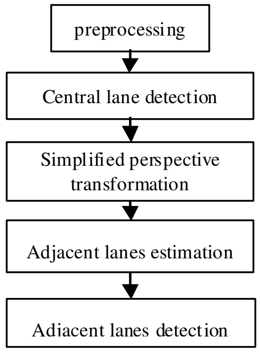
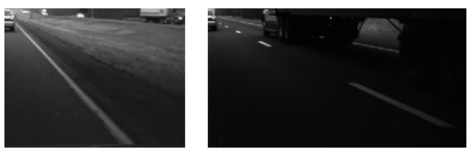


Fig. 1 Flow-chart in case of straight road

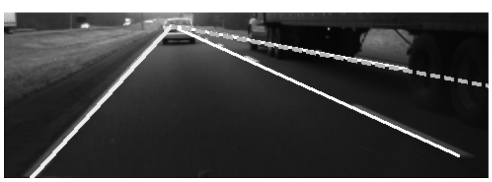
(a)



(b)

(c)

(d)



(e)

Fig.2 steps of lane detection on straight road

Preprocessing consisted of determining the vanishing line in the image and image partition. The vanishing line was used in image partition and the perspective transformation. When the stereo vision camera pair was installed horizontally, the vanishing line could be determined by finding the vanishing point V_P that was the intersection of lane marks. The region of interest (ROI) was the part below V_P in the image. The ROI was then further divided into left and right sections at the column of V_P. And the left section was reversed and the image partition was done (Fig. 2 (b)). Given that lane marks went through the left top of each image section, the image partition simplified the following Hough transformation by limiting the value of parameter ρ (distance from the line to the original). The detection of central lane was the continuous lines in Fig. 2 (c).

Since the angular relationship between lane marks was unknown in the original view, it was required to recover the parallelism of the lanes first. Given the perspective transformation between two views was

$$P_P=HP \tag{1}$$

Where P the point in the original image

P_P the point in the rectified image

H the 9×9 homogenous matrix

H for a complete perspective transformation could be constructed using the camera's installation parameters including its pitch, roll, yaw and height. However, a simplified perspective transformation (an affine transformation actually) was designed in the work for the straight road cases that recovered the parallelism of the lane marks only. The homogenous matrix for the affine transformation was in the form of

$$H=\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ a & b & c \end{bmatrix}$$

Where the vanishing line in the image was represented by ax+by=c [6].

The parallelism-recovered lane marks and the estimation of the two adjacent lane marks were shown as the discrete lines in Fig. 2 (c). It should be noted that the perspective transformation was incomplete. Thus the direction of the lines was not the same with their direction in real world and the interval between lines was meaningless for analysis. The estimations of the adjacent lanes in the original view were obtained by a reverse perspective transformation using H^{-1} (Fig. 2 (d)) and it simplified the detection by limiting the range of parameter ρ and θ (line angle) of the adjacent lanes. As seen in Fig. 2 (e), the right lane marks that were obstructed by the truck were successfully detected.

The center point on the bottom row of the original image was picked up and its position in the lane was calculated. As this point was actually a point on the road in front and the vehicle was overpassing it in the near future, it was approximately considered as a point on the vehicle and used for determining the vehicle's position.

2) The case of curve

Some curve with large radius on highway could be treated as straight lines [7]. However, line detection may fail if it was applied to curve with relatively small radius such as ramp. As a result, the work flow of this case was different from the straight road (Fig. 3). After the edge features were extracted in the original view, a complete perspective transformation based on the camera's installation parameters was performed. Then the points on the central lane marks was detected in the top view image by scanning techniques and the central lane marks was obtained by fitting these point with a circular curve.

(1) Determination of the camera's installation parameters

Camera's pitch, roll and yaw angles were required for the complete perspective transformation from the original view to top view. Existing studies involving such transformation measured these parameters when the camera was installed and treated them as constant. Manually measurement of these parameters was undesired in the proposed system because it complicated the system's installation and the parameters were likely to change during driving.

Instead, these parameters in the system were calculated using image processing with the knowledge of the vanishing line and the image center. According to the camera coordinates and ground coordinates shown in Fig. 4, the roll angle was derived from the slope of the vanishing line in the image. The pitch angle could be calculated in the triangle consisting of the image center, optical center and the vanishing point in the image. The heading angle was rather small during driving and could be set zeros [8]. Note that the three angles were actually approximations of their real value, but the accuracy was acceptable as they were rather small.

(2) Lane detection in top view

After the angles were calculated, the perspective transformation could be done using (3) [9] and the result was shown in Fig. 5 (c).

$$x(u,v)=h\,cos[(\gamma-\beta)+2\beta v(n-1)]/tan[(\theta-\alpha)+2\alpha u(n-1)]+l \quad (3)$$
$$y(u,v)=h\,sin[(\gamma-\beta)+2\beta v(n-1)]/tan[(\theta-\alpha)+2\alpha u(n-1)]+d$$

where [x,y] the point's position in the top view image;

[u,v] the point's position in the original image;

h the height of the camera; [θ, γ] the pitch and heading angle of the vehicle;

[α, β] the camera's aperture angle in horizontal and vertical direction;

[l, d] parameters to adjust the position of the road in the top view image.

Perspective transformation may result in the loss of the pixel in the top view image and this situation deteriorated as the pixel approached the vanishing line that was at the infinite (left image of Fig. 5 (c)). To solve the problems, a dilate-erode operation was applied to fill the spaces between pixel in the image part close to the vehicle (right image in Fig. 5 (c)). Then the point on the lane marks could be detected by scanning the image at each row. Pixels in the image had strong relationship with points in the real world as the perspective transformation was complete. Given that the interval between lane marks was from 3 to 3.7 meters in China, two pixels with interval in this range was picked up as candidates on the lane marks (left image in Fig. 5 (d)). Finally the lane marks were detected by fitting the point candidates with a circular curve.

The estimation of the adjacent lanes could be made by simply offsetting the central lane marks in top view and the detections were not projected back to the original image in the case of driving in a curve.

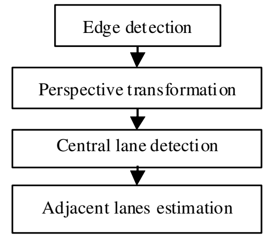


Fig.3 flow chart in case of curve

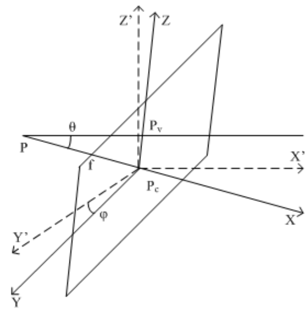
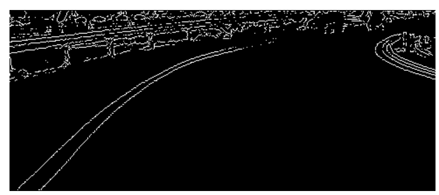
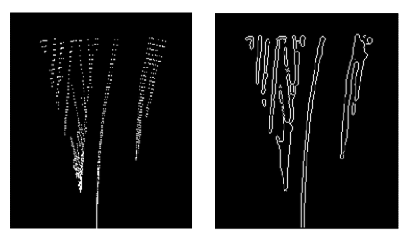


Fig.4 camera coordinates and ground coordinates. x-y-z camera coordinates; x'-y'-z' ground coordinates

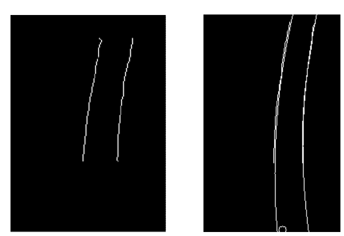
(a)



(b)



(c)



(d)

Fig. 5 steps of lane detection in case of curve

C. experiments and discussions

Image sequences of the Ring 5 highway in Beijing China and I-57 interstate highway USA were used to investigate the system's performance for multiple-lane detection. The time cost for computation was 23ms for curve case and 35ms for straight road. Experimental results implied that when the central lane marks were successfully detected, the estimated adjacent lane marks agreed with their real position (difference up to 3 degrees on straight road).

Problems existed in the following aspects:

(a) Fail in detecting the central lane marks

The detection of the central lane was the basis in the multiple lane detection scheme. However, it may fail in the following two situations: (1) the lane marks were discontinuous and the visible part in the image was insufficient for detection. (2) the existence of preceding vehicles in the same lane interfered the detection. The system output no detection result in the first situation. As this situation only came up occasionally in continuous processing, the loss of individual detection was not harmful. The second situation was more serious because it led to misdetection. Currently, the proposed solution for this problem was informing the system with the existence of preceding vehicle using stereo vision vehicle detection and to eliminating its impact by adjusting the ROI.

(b) Vehicle's position in a curve

It was not suitable to calculate the vehicle's position in the lane when the vehicle was driving in a curve using the same method on straight road. As a demonstration, the center point on the bottom row of Fig.5 (a) was projected to the top view image (circle in the bottom row of the right image in Fig. 5 (d)). This position was obviously not the vehicle's position. This was because the heading direction of the vehicle's body had a considerable bias to the vehicle's actual heading angle (the direction of the front tires) when the vehicle was driving in a sharp curve.

III. CONCLUSIONS

A vision system to detect multiple lanes in structured highway scenario was presented in this paper. The adjacent lane marks were detected based on their estimations that were made by the central lane detection result. Based on the vehicle's GPS position and digital map data, the system recognized if the vehicle was driving on straight road or in a curve and applied different lane detection schemes. For straight road, the central lane was detected using Hough transformation and a simplified perspective transformation was designed to recover the parallelism of the lane marks for estimating the adjacent lanes. When the vehicle was in a curve, a complete perspective transformation was first performed and the central lane was then detected by scanning at each row. Such an "estimate and detect" scheme allowed the system to detect the adjacent lane marks that may be obstructed by other vehicles with high confidence. In addition, the information used in either the simplified or the complete perspective transformation was collected using image processing techniques instead of manual measurement. This simplified the system's installation and enabled the system to update these information during driving. This system served as a part in a stereo-vision vehicle detection system in multiple scenarios.

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