Detecting Road Conditions in Front of The Vehicle Using Off-The-Shelf Camera

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***Abstract*—The development of road transportation makes it easier for people to drive their vehicles. Unfortunately, it also causes the increasing number of traffic accidents. Advanced driver assistance systems, which in many ways is based on the future trajectory prediction of the vehicle, are developed to alert the driver for potential dangers. Road conditions, including road geometry and the distance between lead vehicle and host vehicle, are important factors in improving accuracy of future trajectory prediction. The road conditions can be obtained by the camera affixed in the vehicle. In this paper, we propose an image processing system, which includes a curve detection algorithm (CDA) and a distance conversion (DC) algorithm, to obtain these road conditions from the image. First, CDA detects the lane stripes and calculates the vanishing point. The road trend can then be identified according to the location of the vanishing point. DC is used to convert the distance between the lead and host vehicles in the image to the real distance. Through analyses and experiments, it is shown that the proposed system achieves a higher precision than the baseline algorithms.**

***Index Terms*—Vehicle safety, image analysis, turn detection, distance estimation.**

I. Introduction

The road transportation development encourages more and more people to purchase vehicles. Consequently, the number of traffic accidents also increases significantly in recent years. Major traffic accident in the Republic of China (R.O.C.) is a gruesome sight: a pileup occurred on the Freeway No. 1, which caused the hospitalization of 21 people on June 23, 2016 [1].As a response, the Government of R.O.C. puts more emphasis on the issue of traffic safety. In order to reduce the number of traffic accidents, the government constantly revises the regulations and formulates new policies. In addition, more and more researchers have also studied on the Advanced driver assistance systems (ADAS) [2]. ADAS can enhance vehicle safety by alerting the driver to avoid collision and accident. The value of ADAS can be improved by combining the future path prediction algorithm of the vehicle, such as collision avoidance system [3] and lane change assistance [4].

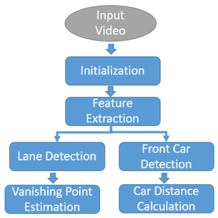
The most common path prediction algorithm is to make use of the GPS sensor [5] to detect the latitude, longitude, speed, and heading of the vehicle, and these detected information are applied to a predefined vehicle motion model. However, this type of the path prediction algorithm fails to deal with unexpected events, because GPS can not provide information about sudden occurrence in front of the vehicle. In other words, the road conditions in front of the vehicle is an useful information which can improve the accuracy of the vehicle path prediction. Although the precise road geometry can be provided by a digital map, it is costly. Therefore, an alternative method is to use a vision sensor mounted in the vehicle to photograph the road in front of the vehicle. The situation of the road, including the road trend and the distance from the lead vehicle to the host vehicle, can be obtained by the image processing technology. The road trend can be identified by the curve detection, and the distance of the lead vehicle can be obtained by converting the distance of the lead vehicle in the image to the real distance.

In [6], Hoang *et al.* proposed a lane detection algorithm based on line segment detector (LSD) [7]. The LSD is supposed to work on any digital image. The lane detection algorithm can be used to discriminate between dashed and solid lanes under various environmental conditions. However, Hough Transform [8] provides more specific line search and is able to combine non-contiguous line segments to a single longer line segment. In [9], Rezaei *et al.* proposed a real-time vehicle detection and inter-vehicle distance estimation algorithm based on monocular-vision techniques. The vehicle detection method is based on Haar-like features, and the distance of lead vehicle is estimated by monocular camera.

In this paper, an image processing system is proposed which combines a curve detection algorithm and a distance conversion algorithm. In curve detection algorithm, Hough Transform is used to detect the lane stripes of the road and calculate the vanishing point. The location of the vanishing point in the image is then used to identify whether the road is curved or not. The distance conversion algorithm is based on the estimated model proposed in [10], which uses trigonometry to calculate the distance between the host vehicle and lead vehicle in the image to the real distance.

The performance of the proposed system is validated via two different datasets, NCU and NST1, as shown in Figure II-B3. A confusion matrix is used to represent the experiment results of our system. Compared with the algorithm proposed in [11], our curve detection algorithm improves the accuracy by 8.9% and 10.7% in each dataset. For our distance conversion algorithm, its accuracy is always higher than 95% when the distance between the host and lead vehicles is within 20 meters.

II. System Design



(a) System Architecture

(b) Line segments within image detected by straight line Hough Transform.

Fig. 1. Driving Route

A. The Basic Idea

In this paper, a camera is affixed to the front of the host vehicle to acquire the images of the road condition. The OpenCV is used to process the images from the camera. The image in front of the host vehicle may provide hints, which help to predict what reaction the driver is likely to take. The information such as the location of the vehicles in front of the host vehicle and the lane stripes extracted from the images are crucial to the vehicle trajectory prediction. The location of the front vehicles can be used to calculate the distance between the host vehicle and the lead vehicles, and lane stripes can be used to determine if the host vehicle follows the curve road in front of it.

The proposed algorithm is used to calculate the vanishing point with lane stripes and use the position of vanishing point in the image to determine whether the vehicle is driving along a curve road. Curve detection is primarily used to determine the condition whether the heading of the host vehicle is changing such as when the host vehicle is making a turn or changing lanes. Additionally, a method is proposed to extract the location of the vehicle in front of the host vehicle in the image, which can then be used to calculate the true distance between the host vehicle and the lead vehicle by using trigonometry. The distance between the lead vehicle and the host vehicle can be used to verify if any of the vehicles in front of the host vehicle is within the safe distance and if the lead vehicle hits break suddenly. Although the image cannot provide information such as latitude, longitude, speed, and heading without additional sensors, these pieces of information obtained by our algorithms can provide some hints to predict if the driver's driving pattern may change. The proposed system is divided into three phases: initialization, feature extraction and validation, and conversion phase. The overview of the proposed system is shown in Figure 1(a). The detail of each phase is elaborated in the following subsections.

B. Curve Detection

1) Initialization: In the initialization phase, we take the bottom half of the image for analysis. Since the features to be extracted (i.e., lane stripes) are located in the lower half of the image, the top half of the image will be removed to reduce the noise. The image is converted to gray-scale, then Gaussian filter is applied to smooth the converted image for Canny edge detection.

2) Feature Extraction and Validation: In the feature extraction and validation phase, the straight line HT detection is used to detect the line segments within the image. The slope of the line segments is calculated, and ignored when the absolute value of the slope is greater than a threshold or when the line segments are close to the horizontal line. According to the location of the midpoint of the line segment relative to the center line of the image, the line segment will be classified differently. For instance, if the midpoint of the line segment is located on the left side of the center line, the line segment will be considered as a left vector. Otherwise, it will be considered as a right vector. The result of the image processed by the straight line HT detection is shown in Figure 1(b).

The line segment in a left vector or a right vector closest to the center line of the image will be selected to estimate the lane stripes of each side. The EMA is used to calculate the average of the selected line segment with the results of the previous images by Equation (**??**). Then, the result of EMA is taken as the new lane stripe of this image, and a slope-intercept form is used to calculate the intersection point of the equation of the lane stripes as a vanishing point.

If no line segment is detected on left or right side of the center line within the image by straight line HT detection, the result of the previous image is used as the result of current image. If no line is detected for five consecutive images, the previous result is no longer used, but N/A is used as the result. The previous results are removed, and EMA is reset.

3) Conversion: In the conversion phase, the current road trend can be identified according to the position of the vanishing point relative to the center line of the image. The location of the vanishing point should be close to the horizon. A vanishing point is valid if the vanishing point is either higher than the horizon or is within a threshold away from the horizon. For a valid vanishing point, its relation to the road trend can be classified as follow:

- When the value of the x-axis of the vanishing point is greater than half width of the image plus an offset, the vehicle is heading toward a right curve.
- When the value of the x-axis of the vanishing point is less than half width of the image minus an offset, the vehicle is heading toward a left curve.
- Otherwise, the vehicle is heading toward a straight road.

If the vanishing point is found to be invalid, the proposed algorithm will be used to search for other line segments within the image to identify the vanishing point again.

C. Vehicle Detection and Distance Calculation

1) Initialization: In the initialization phase, a trained cascade of the feature-based classifier is included from an open source file, cars3.xml, which is usually used to detect the vehicle within the image with OpenCV. The input image is converted to gray-scale and the converted image is smoothed by the Gaussian filter, and the Canny edge detection is used to obtain the edge of the image.

2) Feature Extraction and Validation: In the feature extraction and validation phase, the Haar-like feature cascade classifier is used to detect the features of vehicles within the

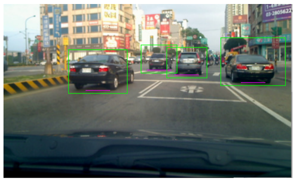


Fig. 2. Vehicle Detection

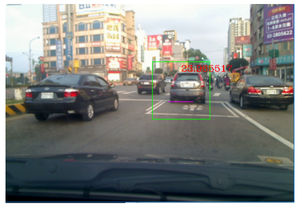


Fig. 3. Front vehicle distance calculation.

(a) Driving route of NCU

(b) Driving route of NST1

Fig. 4. Driving Route

image. The extracted feature is a small rectangular region. The method proposed by [11] is used to determine the features of the real vehicles from all of the extracted features. The region of the features extracted by the cascade classifier are used to compare with the regions corresponding to the image which is processed by edge detection. If the number of horizontal edges in a corresponding region is greater than a threshold, the feature is considered to belong to the real vehicle. The position of the upper left and the bottom right corners of the region and the location of the vehicle are stored in a vehicle vector. The location of valid vehicles obtained from the image is shown in Figure 2.

3) Conversion: After the position of the lead vehicle within the image is obtained, a distance estimation model proposed in [10] is used to calculate the distance between the host vehicle and the lead vehicle. Basically, the distance of the host vehicle and the lead vehicle in the image is converted to the real distance between the host vehicle and the lead vehicle by trigonometry. Equation (1) based on the above model is used for the conversion of the distance.

$$d_2 = \frac{H_c * e_v}{P_r * (Y_{HV} - v_0)} - d_1, \tag{1}$$

where H_c is the height of camera from the ground, e_v is the focal length of camera, d_1 is the distance between the camera and the front of the host vehicle, v_0 is half of the width of the image, D is the distance between the camera and the back of the lead vehicle, d_2 is the distance between the front of the host vehicle to the back of the lead vehicle, P_r is the length of a pixel on image sensor, and Y_{HV} is the value of y axis of the lead vehicle in the image. The result of distance between the host vehicle and the lead vehicle is shown in Figure 3.

III. Performance and Evaluation

A. Experimental Setup

1) Data Collection: The experiment was conducted on the roads surrounding National Central University (NCU) and Taiwan North-South Throughway (NST) with a web camera and a GPS sensor. The camera is affixed to the front of the rear mirror in the host vehicle to acquire the images of the road condition. The GPS sensor is ITRI WAVE/DSRC Communications Unit version 4.4 OBU provided by Industrial Technology Research Institute, which is used to collect the location information of the host vehicle.

Two datasets are collected to determine the increased accuracy of vehicle trajectory prediction. The driving routes of these two datasets (NCU, NST1) are shown in Figure II-B3. The route, NCU, shown in Figure 4(a) contains the roundabout roads of NCU. The driving routes NST1, shown in Figure 4(b) follows a straight line then curve to the right.

2) Simulation Configuration: In the simulation, all algorithms, including curve detection and distance conversion, are implemented. In our system, the sampling rate of the image and GPS data is 0.1 second.

Two different metrics are used to analyze the performance of our system: the error rate of curve detection, and the error rate for the distance conversion.

The data collected from GPS sensor is considered as the ground truth of the experiment. The images taken by the camera are used to detect the curve by detection algorithm. A 3 x 3 confusion matrix is used to represent the comparison result of the ground truth with the result of the curve detection algorithm.

In the experiments, the confusion matrix is used to distinguish the road condition between Right curve, Straight road, and Left curve. The ground truth is used as the actual value of the confusion matrix and the result of the curve detection algorithm is used as prediction value. The error rate of the distance conversion algorithm is calculated by the converted distance of the image and the ground truth. In the experiments, the camera is placed at the height of 1.2 meters from the ground. The road is marked every 5 meters starting at the distance of 1 meter from the camera (the distance of the camera to the front of the car is 1 meter) and the marks are used as the ground truth in our experiment.

B. Simulation Results and Analysis

To verify the performance of our curve detection algorithm (CDA), the CDA and the lane detection algorithm (LDA) proposed by [11] are compared. The differences between the CDA and LDA are listed as follows.

- CDA selects the line segment which has a midpoint closest to the image center as the lane stripe. There are two steps in LDA in selecting the lane stripe. First, the algorithm selects the line segment which has maximum number of white pixels around the line segment in edge detection. Second, the algorithm selects the line segment closest to the center of the image when the value of the y axis is half the height of the image.
- LDA uses the variations in values of the slope and intercept of the lane stripe to determine whether the line segment is reasonably selected; while CDA uses the value of y axis of the intersection of the lane stripes.

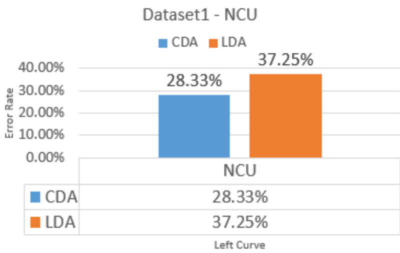


Fig. 5. Error rate - NCU

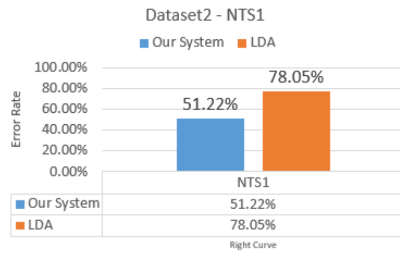


Fig. 6. Error rate - NST1

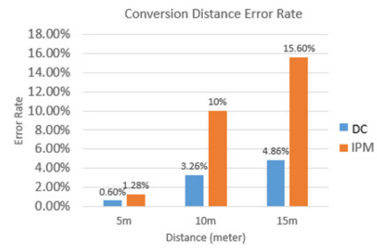


Fig. 7. Error rate - Distance conversion

TABLE I
CONFUSION MATRIX - NCU

(a) CDA

NCU	Right	Straight	Left
Right	9	138	82
Straight	1	483	46
Left	60	156	672

(b) LDA

NCU	Right	Straight	Left
Right	37	89	103
Straight	23	345	159
Left	159	72	637

TABLE II
CONFUSION MATRIX - NST1

(a) CDA

NST1	Right	Straight	Left
Right	82	242	5
Straight	11	503	23
Left	9	251	23

(b) LDA

NST1	Right	Straight	Left
Right	63	259	7
Straight	13	288	136
Left	18	231	34

Table I and Table II lists the result of comparison between the two algorithms and the ground truth in the NCU, and NST1 datasets, respectively. It can be observed that in all datasets when the CDA is used, the number of the following two types of incorrect results are obviously reduced:

1) When the ground truth is Right curve, the result of CDA is Left curve.
2) When the ground truth is Left curve, the result of CDA is Right Curve.

For CDA, the number of times that the ground truth is Left or Right turn but the detection results is Straight road is relatively high. The reason is that although the vehicle travels on a straight road, it may make lane changes or other maneuvers involving turning the steering wheel. This results in the change of the heading of the host vehicle, and the ground truth becomes Left or Right curve. When the ground truth is a straight line, the number of incorrect detection of LDA is significantly higher than the CDA. It is because that LDA cannot make the correct detection immediately when the host vehicle is at the beginning or in the end of the curve. However, CDA does not have such an issue.

Figure 5 and Figure 6 illustrate error rate of CDA and LDA algorithms in these two datasets. The results show that the error rate of CDA is at least 8% less than that of LDA.

To assess the performance of the distance conversion (DC) algorithm, it is compared against the Inverse Perspective Mapping (IPM) algorithm. Table III shows the result of comparison between DC and IPM. When the real distance is 20 meters, the error rate of our algorithm is less than 5% while the error rate of IPM is greater than 15%. The error rates of DC algorithm and IPM algorithm are shown in Figure 7.

TABLE III
ACCURACY OF DISTANCE CONVERSION

Real	DC	DC Error	IPM	IPM Error
10m	9.9403m	0.0597m	10.128m	0.128m
15m	15.4883m	0.4883m	13.484m	1.516m
20m	19.0286m	0.9714m	16.88m	3.12m

IV. CONCLUSIONS

In order to improve the accuracy of path prediction, a camera affixed in the host vehicle can be used to obtain the road information in front of the host vehicle. In this paper, we propose a system to detect the curve and calculate the distance between the host and lead vehicles. First, CDA is used to detect the lane stripes and calculate the location of the vanishing point, and the road trend can be derived. Once the road trend has been obtained, driving conditions such as the switching of lanes or the following of a curve can be identified when the heading of host vehicle changes. Second, by detecting the position of the lead vehicle within the image, DC can be used to convert the distance from the image to the real distance. Compared with the baseline algorithm, the accuracy of CDA improve at least 8.9% in our experiment. Additionally, the accuracy of DC algorithm is higher than 95% when the real distance between host vehicle and lead vehicle is within 20 meters.

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