Integration of Vehicle and Lane detection for Forward Collision Warning System

Huieun Kim, Youngwan Lee, Taekang Woo, and Hakil Kim
Graduate School of Information and Communication Engineering, Inha University
Incheon, Korea
Email: {hekim, yw.lee, tkwoo}@inha.edu, hikim@inha.ac.kr

***Abstract*—The capability of automated vehicles with intelligent on-board systems aimed at improving traffic safety has been in constant advance. This paper proposes an integrated module of lane and vehicle detection for a forward collision warning system that can be embedded in an autonomous driving system operating in real time. Integration of lane and vehicle detection provides more precise information for driving environments by using geometric consideration of the roads, and achieves synergistic effects for rejecting false alarms by adjusting ground constraints. Also, once the vehicle is localized in ego-lane, it is able to estimate the distance between the front and ego-vehicle. The experimental results in this paper, conducted on a real road dataset, verify the applicability of the proposed work for advanced driver assistance systems.**

***Keywords*—Autonomous Driving;Vehicle Detection, Lane Detection, Integrated system, Embedded system**

I. Introduction

Because of the increase in demand for vehicles, intelligent systems for autonomous driving have been developed to enhance traffic safety and driving comfort. One of the representative devices for safe driving is an advanced driver assistance system (ADAS) that can contribute to making better decisions in the middle of traffic.

Research on computer vision for on-road safety have involved monitoring objects exterior to the vehicle like lane estimation, traffic sign classification, pedestrians, and vehicle detection. Such algorithms derive more precise information for drivers when they are combined. For example, [1], [2] suggest efficient lane and vehicle detection from integration synergy. By applying both lane position and vehicle location to each of the detection measures, both false positive rates decreased.

Forward collision warning systems (FCWS) are one key technology for intelligent vehicles. Frontal crashes account for about 55% of all traffic accidents with fatalities and serious injuries involving passenger cars [3]. To avoid such accidents, FCWS detects the vehicle ahead and calculates the distance between the driver and that vehicle. As the demand for such systems has risen, various aspects of the applications for FCWS have appeared. Research about FCWS usually makes assumptions based on embedded operating systems such as smart phones [4]. In another case [5], a stereo camera was used to calculate the distance ahead of the FCWS device. However, smartphone based driver assistance system can easily be interrupted by exterior conditions and intervening contacts. Also, applications requiring stereo cameras have the problem of significant expense for installation and utilization.

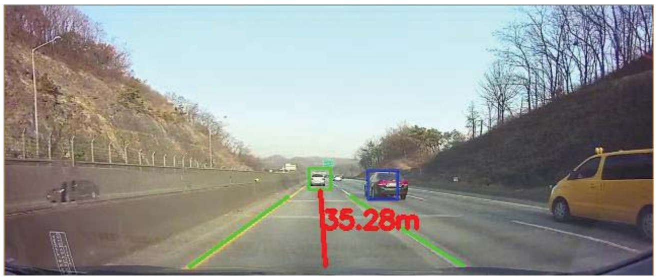

Figure 1. Result of the integrated module for FCWS

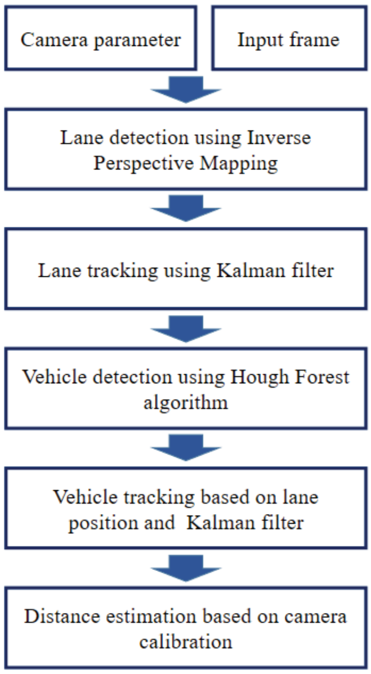

Figure 2. Overall process of integrated module.

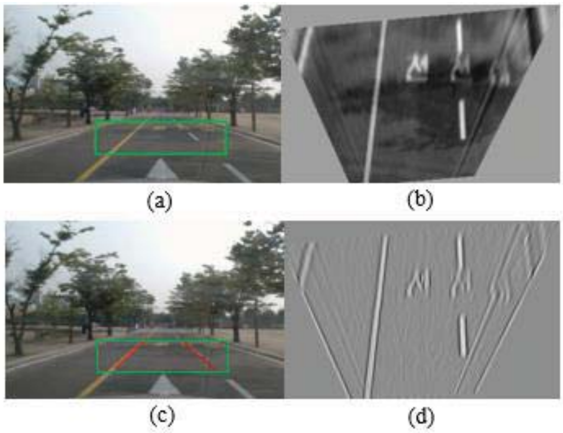

Figure 3. Representation of lane detection process: (a) Original image with green ROI. (b) IPM image. (c) Result of lane detection. (d) Filtered IPM image.

Therefore, this paper suggests an integrated module for FCWS that overcomes the problems mentioned above and makes possible cost-effective, real-time processing. The main contributions of the work are as below:

- Recognition module based on integration of lane and vehicle detection, which provides greater refinement of recognition of real roads.
- Distance estimation based on a single-camera calibration model that provides content using a low cost device rather than higher priced sensors.
- Real time processing on an NVIDIA TK1 embedded board that confirms the applicability of the proposed application.

II. Integrated Module for a Forward Collision Warning System

The main components of the proposed method are an integrated detection module and distance estimation. Fig.2 denotes the overall process carried out by the integrated module. It adopts inverse perspective mapping for lane detection and Hough forest for vehicle detection. Details of the integrated detection are as follows.

A. *Lane detection*

The lane-detection algorithm is composed of a detection stage and tracking stage. Using the input camera parameters, regions of interest (ROI) for lane detection are determined. Based on inverse perspective mapping (IPM), lanes are detected lane in the fixed ROIs. After that, multiple lane candidates are verified using the Kalman filter and the lanes for the next frame are estimated. Fig.3 represents the intermediate and final results of lane detection using IPM.

B. *Vehicle detection*

The proposed vehicle detection method includes hypothesis generation (HG) and hypothesis verification (HV), as in other research [6]. Regarding HG, an appearance-based algorithm is used to produce vehicle candidates. This paper applies the Hough forest algorithm [7], which is a part-based object detection method robust on occlusion. From the resultant image from the Hough forest algorithm, which represents the

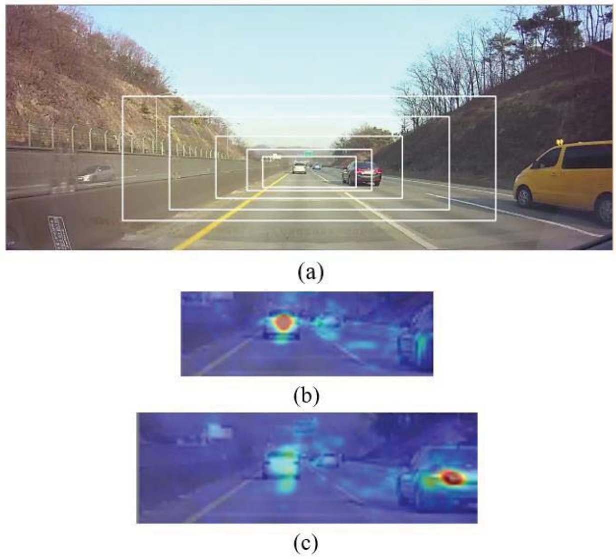

Figure 4. Pyramids in vehicle detection and accumulated probabilistic images: (a) Original image with white ROIs that covering each region on 15, 20, 30, 45, and 60 m ahead of the camera. (b), (c) Accumulated probabilistic image of ROIs that representing 45 and 60 m location.

cumulated probability of a vehicle, the center of vehicle is localized and the first candidates are derived. In this process, exterior demonstrations such as edge and LAB color features were trained using the Hough Forest method.

The first step of vehicle detection is to build pyramids according to the distance information. Fig.4 shows the ROIs located on 15, 20, 30, 45, and 60 m ahead of the camera. The vehicle detection algorithm generates the accumulated probabilistic image that visualizes the location of vehicles according to equations (1) and (2) [7]:

$$p(E(X)|I(Y):\{T_c\}_{x=1}^{\tau}) = \frac{1}{T}\sum_{\delta=1}^{\tau} P(E(X)|I(Y):T_\delta), \quad (1)$$

$$V(X) = \sum_{\delta=1}^{\tau} P(E(X)|I(Y):T_\delta), \quad (2)$$

Then in the HV process, by enforcing geometrical constraints, the vehicle candidates are verified.

C. *Vehicle tracking based on lane position and distance estimation*

Location and tracking of vehicles within the ego-lane, contributed by the lane detection module, provide a fundamental framework for monitoring the frontal vehicle. The formulas for calculating the vehicle in ego-lane is as follows:

$$y_c < S_l \times (x_c - x_{ls}) + y_{ls} \quad (3)$$

$$y_c < S_r \times (x_c - x_{rs}) + y_{rs} \quad (4)$$

$$S_l = \frac{y_{ls} - y_{le}}{x_{ls} - x_{le}} \quad (5)$$

$$S_r = \frac{y_{rs} - y_{re}}{x_{rs} - x_{re}} \quad (6)$$

(x_c, y_c) denotes the center coordinate of the vehicle bounding box. From lane detection module, we can have the two

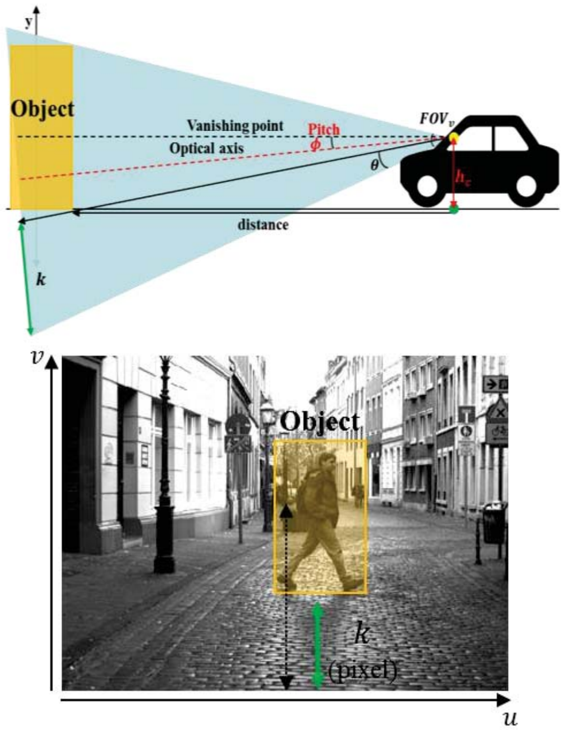

Figure 5. Mono Vision Distance Measurement Model (Top). Object in Image (Bottom).

dimensional coordinates of the lane. (x_{ls}, y_{ls}) and (x_{rs}, y_{rs}) indicate the coordinates of start position of left and right lane while (x_{le}, y_{le}) and (x_{re}, y_{re}) represents the positions of end point of left and right lane. In (5) and (6), we have S_l and S_r that are slop of each left and right lane. Based on (3) and (4), we can classify the frontal vehicle in each lane. By tracking vehicles in three forward lanes, the accuracy of vehicle tracking can be improved.

Furthermore, by calculating the distance between the driving vehicle and the forward vehicle in the ego-lane, a forward collision warning can be determined based on a look-up table. For distance estimation, the relation between camera coordinates and standard coordinates is considered. We applied a mono-vision distance measurement model that calculated the distance of objects using camera calibration information such as intrinsic parameters and extrinsic relationships between the standard coordinates. The mono-camera-based distance estimation model operates like Fig.5. This model makes an assumption on planar ground because there are limitations when representing the real 3D-world using a single 2D-image coordinate [8].

The formula derived by intrinsic and extrinsic parameters of the camera is used for calculating the numerical space between the object and the camera:

$$\theta = \frac{FOV_v}{resolution_y} \times k \tag{7}$$

$$\frac{h_c}{d(k)} = tan(\frac{FOV_v}{2} - \theta) \tag{8}$$

$$d(k) = h_c \times cot(\frac{FOV_v}{2} - \frac{FOV_v}{resolution_y} \times k) \tag{9}$$

$$d(k, \phi) = h_c \times cot(\frac{FOV_v}{2} - \frac{FOV_v}{resolution_y} \times k - \phi) \tag{10}$$

Regarding the bottom of object as the space between camera and object, the angle θ can be measured as in (7). Each FOV_v and $resolution_v$ denotes a vertical field of view and v-axis resolution of the image expressed in (u, v) coordinates. Here, k expresses the pixel difference between the bottom of the image and the bottom of the object. In (7), the formula represents the relationship between the distance to the object and the height of the camera fixed on the car. Moreover, h_c and $d(k)$ also denotes the height of the camera fixed on the car and the distance to the object in the real-world. Using (7) and (8), an interaction formula between the distance and image coordinates can be deducted. The pitch angle of the camera is applied in (9), in the form of (10). Fig.1 shows the result of the integrated module and distance estimation for the frontal vehicle.

III. EXPERIMENTAL RESULT

A. Detection experiment

In this paper, a dataset from Inha university was used to evaluate the detection modules in real road scenarios that involved a variety of illuminance environments. The dataset was taken by a camera attached between the rearview mirror and the vehicle windscreen. It includes the driving environment around Incheon, Korea under various weather conditions.

Table I shows the lane detection results from each scenario. The average precision of lane detection was 95.2% and the false positive rate (FPR) was 0.04, which shows a reliable range of error. Vehicle detection also achieved 87.4% accuracy. In addition, the FPR of the integrated module showed a decrease of

TABLE I. DETECTION ACCURACY OF LANE DETECTION MODULE

Dataset	Conditions		Precision	FPR
Inha	Urban	Rainy	0.94	0.06
		Clear	0.94	0.05
	Expressway	Sunset	0.94	0.059
		Cloudy	0.99	0.001

TABLE II. DETECTION ACCURACY OF VEHICLE DETECTION

Dataset	Conditions		Vehicle detection only	
			precision	*FPR*
Inha	Expressway	Cloudy	0.825	0.21
		Clear	0.923	0.06
		Foggy	0.875	0.13

TABLE III. DETECTION ACCURACY OF VEHICLE DETECTION

Dataset	Conditions		Vehicle detection integrated with Lane detection	
			precision	*FPR*
Inha	Expressway	Cloudy	0.801	0.18
		Clear	0.926	0.03
		Foggy	0.877	0.12

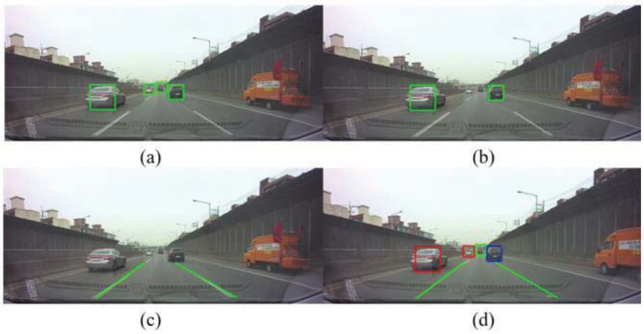

Figure 6. Illustrating vehicle detection result with lane and without lane. (a) Vehicle detection result without lane information. (b) Result of vehicle tracking and clustering without lane information. (c) Lane detection result. (d) Vehicle detection result with lane information. We note that assigning the vehicles from each lane separately improves accuracy in clustering and tracking.

7% against all the result of the vehicle detection module in Table II. Integrating the lane context with vehicle detection leads to better accuracy in tracking and clustering, and the combined result is shown in Fig.6.

B. Distance measurement

For evaluating distance estimation error, Daimler Pedestrian Dataset was used [9]. The dataset includes gray images, 2D bounding boxes and 3D positions of people. Each values of yaw and roll are assumed as zero and also the ground is assumed as planar plane. Distance measurement is experimented on two parts among 13,410 frames of the dataset. Part1 (2,700 frames) represents narrow alley environment where the people appear in close range while Part2 (10,710 frames) is consists of general roadway.

TABLEⅣ. AVERAGE OF EACH ALGORITHM DISTANCE ERROR

Error rate(%)	Part 1	Part 2
Mono Vision	12.920	18.768

Fig.7 indicates that error rate increases sharply in distance over 20m. For example, 10% error in 20m distance means that the actual distance of object is 18m to 20m. The error is resulted by the change of pitch angle from uneven surface of the ground. Table Ⅳ shows average error rate of distance estimation module. Based on the assumption on planar plane, the error of estimated distance increased in farther distance.

C. Processing time

The processing times for lane and vehicle detection are (respectively) 3.46 and 28 msec, with a Cores i5-4670 (3.40 GHz), 16GB RAM. The integrated implementation takes 32.25 frames per second (fps), achieving a real-time process. When the work is imported to an NVIDIA TK1 board, the program executes at the speed of 6 fps.

IV. CONCLUSIONS

This paper proposes an integrated approach to FCWS, which is a unified module for ADAS. The proposed model is simple to apply and efficiently uses contextual information from real road

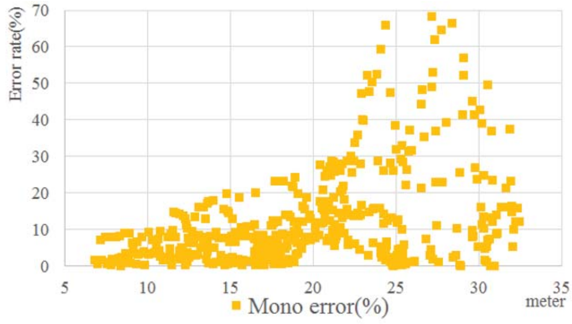

Figure7. Error Rate of Mono vision distance measurement

surroundings. Future work will include extensive tests on real urban roads that involve more complex driving environments.

V. ACKNOWLEDGEMENTS

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