Lane Estimation Algorithm Based on Sensor Fusion Database

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***Abstract*— This paper presents a lane estimation algorithm to recognize the position of the vehicle and the total number of lanes on the road. For more efficient self-driving and ADAS, it is important to recognize ego-vehicle position using environmental sensors. This algorithm provides more convenient services based on precise position of ego – vehicle. The study was based on an actual driving database and algorithm is designed according to various road conditions. The test results with actual driving data showed high accuracy of proposed algorithm.**

Keywords- Recognition; Judgement; Algorithm; Lane Estimation; Accuracy;

Ⅰ. INTRODUCTION

Advanced Driver Assistance Systems (ADAS) have been commercialized to enhance convenience and safety for motorists driving cars, and the prevalence of streamlined electric systems worldwide is increasing. Location determination technology that estimates the location of cars is essential for self-driving cars and ADAS. The sensorconverged positioning system uses a method to estimate the location of the ego-vehicle by converging precision maps with the environment-aware sensors (camera, lidar, radar, etc.) along with Global Positioning System (GPS) and Inertial Measurement Unit (IMU).

Once the location of the ego-vehicle is known correctly, a variety of technologies, such as environmental awareness, vehicle control optimized for the surrounding terrain, and change of driving strategy according to the terrain can be carried out more effectively. One of the most widely used location determination technologies is the radio navigation system that uses satellite information, such as GPS. While this method provides an absolute position in the earth's coordinate system and has the advantage of not accumulating depends on the radio wave receiving situation. To compensate for the increasing number of errors over time, inertial navigation methods such as IMU are being used. Although this approach has the advantage of providing a precise relative position at a short distance, regardless of the radio reception situation, the problem is that the error continues to increase with time due to the limitations of the cumulative-based position estimation method. To overcome the limitations of these existing methods, a recent active study of sensor fusion based precision measurements is performed in [1] and [4]. In general, sensor fusion based precision vehicle location system uses a method to estimate the location of ego-vehicle by converging precision maps with environmental recognition sensors (camera, lidar, etc.) along with GPS and IMU. However, studies have not yet been done to estimate the lane of ego-vehicle in these papers. So, this paper focused on estimating the lane of ego-vehicle and carried out the study. Pre-recognition of the lane information that the ego-vehicle is driving will help the driver of the normal driving, or the driver of the self-driving control system to provide more efficient driving. To further enhance the performance of the lane estimation algorithm, a study was made in [3] on the direction of improvement of lane assessment that provided an integrated framework for lane estimation clues.

Existing studies [1]-[4] used a sensor fusion based precision vehicle location system to pinpoint the position of the ego-vehicle, but proposed algorithm designed a algorithm to estimate the position of the lane under which dynamic obstacles are located on the roadway's lane and the position of the carriage is unrecognizable. Algorithm designed in this study uses relative vehicle information from pre-collected database to estimate the lane of the egovehicle based on lateral distance from dynamic obstacles around the ego-vehicle. For the verification of algorithm, the performance evaluation was conducted on the actual driving environment data of eight roads extracted from the database, and it was found that the lanes of the ego-vehicle could be estimated relatively accurately even when the total number of lanes of the road is not known.

Ⅱ. DATABASE CONSTRUCTION

The vehicles used in this study are constructed from Figure 1. by attaching environmental sensors (LIDAR, RADAR, and CAMERA) to the KIA Carnival vehicles. The Spatial Information Research Institute collected actual driving data from the Ansan Expressway in South Korea to the set up the database and provided this database in order to support the algorithm.

The sensors that are mounted include environmental recognition sensors (five Lidar, three Radar, six Camera) and location recognition sensors (two INS/DGPS [VRS RTK],

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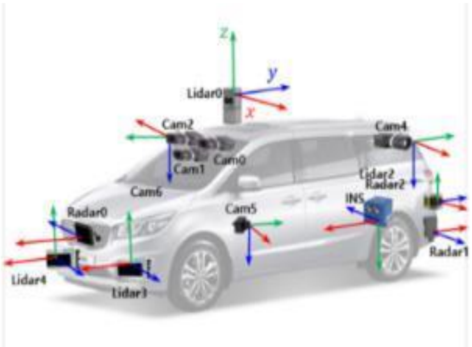
and two DMI and OBD). The information used primarily in this study is the x-axis lateral coordinates. Extracted the relative vehicle coordinate information of around the ego-vehicle shows that it has relative distance and direction from the ego-vehicle.



Object_ID	CenterX	CenterY	CenterZ
25	-10	-955	-149.582
41	50	1175	-73.2534
87	-385	-3280	-216.014
90	750	2460	-37.3392
91	20	1990	-4.68465
92	-380	-2495	-128.359
93	355	1660	-69.7688
94	-310	-5120	-264.192
95	695	1015	-93.9234

Figure 1. Data Acquisition System & X coordinates information

Ⅲ. ALGORITHM DEVELOPMENT

The components of the coordinate system set in the reference car are directional with **x**, **y** and **z**, and these coordinate systems are used to recognize the dynamic obstacles around the ego-vehicle. Algorithm uses the lateral components of the x-axis coordinates and the relative vehicle information recognized around the ego-vehicle.

The difference in distance between the self-vehicle and the perceived center of the adjacent relative vehicle is shown in Figure 2. A condition-based algorithm was developed to estimate the lane where the ego-vehicle is located by extracting the distance difference between the ego-vehicle and the recognized adjacent relative vehicle.

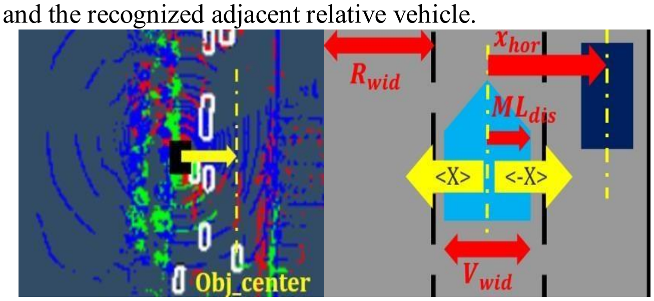


Figure 2. Algoribthm development environment

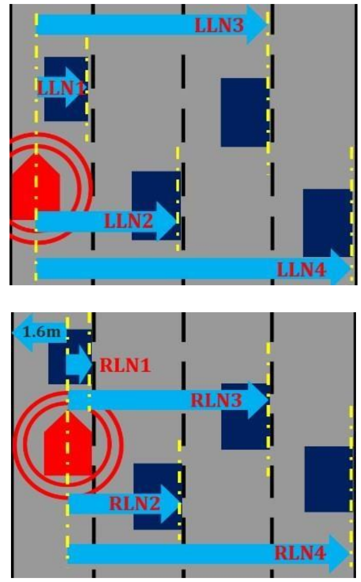


Figure 3. Lane Numbers and Parameters

Depending on the driver's driving habits, the vehicle may be driven on the left side of the road or on the right. In each case, there is a positional difference of the ego-vehicle The parameter $\boldsymbol{X_{hor}}$, suggested in the algorithm of lane estimation in the ego-vehicle is the lateral distance information between the ego-vehicle extracted from the database and the relative vehicle in the vicinity of the ego-vehicle.
$\boldsymbol{R_{wid}}$ is the width of the road, $\boldsymbol{V_{wid}}$ is the width of the vehicle, $\boldsymbol{ML_{dis}}$ is the distance from boundary of the ego-vehicle to the center, (1)**LLN1**, (2)**LLN2**, (3)**LLN3**, (4)**LLN4** are the corresponding parameters for when the vehicle is driven on the left side of the lane. (1), (2), (3), and (4) means how many lanes are present depending on the value of the distance between the ego-vehicle and the perceived relative vehicle.
(1) means that there is one lane between the ego-vehicle and the perceived relative vehicle, (2) two, (3) three, (4) four lanes. (5) **RLN1**, (6) **RLN2**, (7) **RLN3**, (8) **RLN4** are corresponding parameters for when the vehicle is driven on the right side of the road. (5), (6), (7), and (8), likewise indicate how many lanes exist between the ego-vehicle and the recognized relative vehicle, with the number of lanes as shown in the parameter name exists between the ego-vehicle and the relative vehicle around the recognized ego-vehicle.

The width of the road, LN1,2,3,4 was constructed by using the distance of the number of lanes, and if the relative vehicles are located at the width of the lane classified according to the number of lanes, the roadway on which the ego-vehicle is driven can be estimated. The road width was set to any value because the exact road information for the data collection section was not known, the parameters presented are expressed in Figure 3.

TABLE Ⅰ. ESTIMATION ALGORITHM FOR EACH LANE

Road type	Estimated Lane	Estimation Algorithm: Ego-vehicle Left	Estimation Algorithm: Ego-vehicle Right
Four Lane Road	1st Lane	-LLN3 < x_{hor} < -LLN4 && (-LLN2 < x_{hor} < -LLN3 $\Vert$ -LLN1 < x_{hor} < -LLN2)	-RLN3 < x_{hor} < -RLN4 && (-RLN2 < x_{hor} < -RLN3 $\Vert$ -RLN1 < x_{hor} < -RLN2)
	2nd Lane	-LLN2 < x_{hor} < -LLN3 && (-LLN1 < x_{hor} < -LLN2 $\Vert$ RLN1 < x_{hor} < RLN2)	-RLN2 < x_{hor} < -RLN3 && (-RLN1 < x_{hor} < -RLN2 $\Vert$ LLN1 < x_{hor} < LLN2)
	3rd Lane	RLN2 < x_{hor} < RLN3 && (RLN1 < x_{hor} < RLN2 $\Vert$ -LLN1 < x_{hor} < -LLN2)	LLN2 < x_{hor} < LLN3 && (LLN1 < x_{hor} < LLN2 $\Vert$ -RLN1 < x_{hor} < -RLN2)
	4th Lane	LLN3 < x_{hor} < LLN4 && (LLN2 < x_{hor} < LLN3 $\Vert$ LLN1 < x_{hor} < LLN2)	RLN3 < x_{hor} < RLN4 && (RLN2 < x_{hor} < RLN3 $\Vert$ RLN1 < x_{hor} < RLN2)
Three Lane Road	1st Lane	-LLN2 < x_{hor} < -LLN3 && -LLN1 < x_{hor} < -LLN2	-RLN2 < x_{hor} < -RLN3 && -RLN1 < x_{hor} < -RLN2
	2nd Lane	-LLN1 < x_{hor} < -LLN2 && RLN1 < x_{hor} < RLN2	-RLN1 < x_{hor} < -RLN2 && LLN1 < x_{hor} < LLN2
	3rd Lane	RLN2 < x_{hor} < RLN3 && RLN1 < x_{hor} < RLN2	LLN2 < x_{hor} < LLN3 && LLN1 < x_{hor} < LLN2
Two Lane Road	1st Lane	-LLN1 < x_{hor} < -LLN2	-RLN1 < x_{hor} < -RLN2
	2nd Lane	RLN1 < x_{hor} < RLN2	LLN1 < x_{hor} < LLN2
One Lane Road	1st Lane	-LLN1 < x_{hor} < RLN1	-RLN1 < x_{hor} < LLN1

A lane width section of 1st, 2nd, 3rd, 4th means the number of lanes existing between the ego-vehicle and recognized relative vehicle. The estimated result of the algorithm depends on how many lanes are existed between the ego-vehicle and the recognized relative vehicle. expressed in TABLE Ⅰ. The method of applying the extracted relative vehicle information to algorithm will be explained after looking at a Figure 4.

The process of estimating a lane is presented in Figure 4. First extract the lateral distance coordinates of the recognized relative vehicle around the ego-vehicle from the database. Convert the extracted coordinates to the distance value of the (meter) unit and apply them to the algorithm. Then, it is necessary to verify that the distance values of the relative vehicles around the ego-vehicle were in the lane width section given in the algorithm. If the relative vehicle is recognized in the road width section of the algorithm, then the lane of the self-vehicle is estimated, but if it is not recognized, it is reapplied to the algorithm or cannot be estimated to lane of ego-vehicle. The data applied to the algorithm was collected from the reference vehicle (Figure 1) and brought to the file format. It also provided a viewer program that allows users to view data from the Spatial Information Research Institute, which has collected sensor data. Therefore, information such as distance, coordinates, etc. regarding objects around the ego-vehicles is provided in the form of CVS files. Currently, data is applied offline to the algorithm and automatically performed to estimate the position of the ego-vehicle.

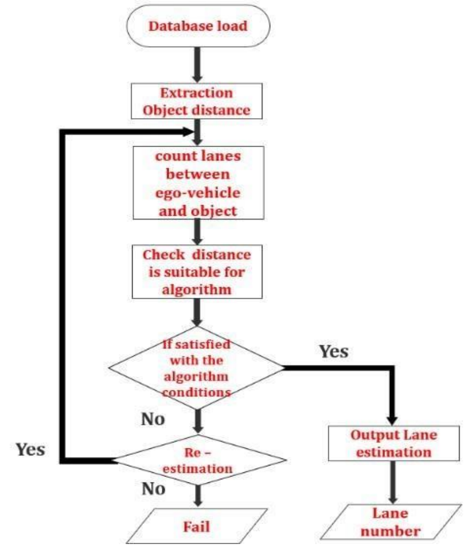


Figure 4. Lane estimation Algorithm

Ⅳ. ALGORITHM VERIFICATION RESULTS

For performance evaluation of developed algorithm, curved roads, tunnels, 1,2,3,4 lane roads, overpass and roads with curvature sections were extracted from the database and shown in Figure 5.

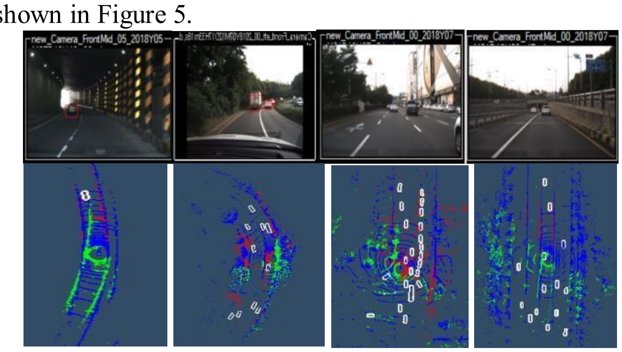


Figure 5. Tunnel, Curve, Overpass, Multi lane Road

The performance evaluation was conducted by comparing the result of lane estimation algorithm for vehicles developed in this study with actual driving data. The evaluation environment was established with 71 specific point-in-time driving data sections extracted from the database and eight types of roads. For each section of the driving data, the accuracy was shown by comparing the actual ego-vehicle lane to the lane estimated by algorithm.

For example, an evaluation of performance at a specific point in time shows that the lane of the ego-vehicle estimated

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by the algorithm is second lane and coincides with the lane of the ego-vehicle actually located when compared with the actual driving data. Such fact can be found in Figure 6. By the above evaluation method estimated the lane from 71 actual driving data specific points-in-time.

As a result of the estimation, the accuracy of the algorithm is divided into Known, which knows the total number of lanes on the road, and unKown, which has no information on the number of lanes. TABLE Ⅲ shows the accuracy of whether the lane estimated by the vehicle algorithm matches the lane in which the vehicle is located in the actual driving data.

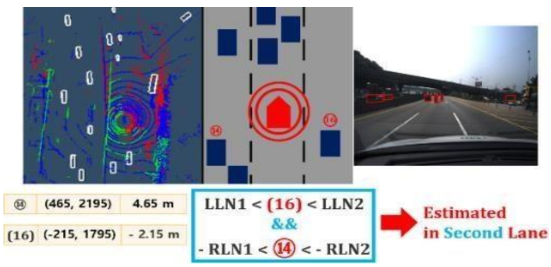

Figure 6. Lane estimation result from algorithm at a specific section in database

TABLE Ⅱ. PARAMETER NAME & VALUE

Parameter \ Value	Ego-Vehicle Left	Ego-Vehicle Right
V_{wid}	1.9 m	
R_{wid}	3.5 m	
ML_{dis}	0.95 m	
LLN1 \ RLN1	2.55 m	0.95 m
LLN2 \ RLN2	6.05 m	4.45 m
LLN3 \ RLN3	9.55 m	7.95 m
LLN4 \ RLN4	13.05 m	11.45 m

TABLE Ⅲ. LANE ESTIMATION ALGORITHM ACCURACY

Position \ Classification	KNOWN	UNKNOWN
	Accuracy [%]	
1st Lane	19/20 [95 %]	13/20 [65 %]
2st Lane	20/22 [90.9 %]	5/22 [22.72 %]
3st Lane	19/21 [90.48 %]	11/21 [52.38 %]
4st Lane	6/8 [75 %]	4/8 [50 %]
Total	90.14%	46.48%

Ⅴ. CONCLUSION

The algorithm verification of 71 actual driving data sections showed high accuracy, with **90.14%** case knowing the total number of lanes and **46.48%** not knowing the total number. Therefore, if there were no dynamic obstacles on top of all lanes, it was not possible to distinguish whether the lane on which the ego-vehicle is located was a second or a third. The reason for the decrease in unknown accuracy is that if the total number of total lanes are not known, objects on other roads can be recognized. This satisfies the various conditions of the algorithm and results in multiple lanes. However, if one continues to build previous lane data to the time axis, it can distinguish this case unless ego-vehicle is rapidly changing lane. Using the estimated lane information from the previous lanes of the stacked data every hour, the estimated results will be much better in any case. This research is still a work in progress, but in the future studies we will use a more flexible and accurate kalman filter or particle filter than a specific condition-based algorithm, The estimation algorithm with these filters will also be able to estimate the curve roads on which the curvature exists. Finally, the autonomous vehicle "**D2**" held by the Autonomous a2z will be used to collect data directly from specific sections and apply the algorithm developed to the actual vehicles to verify the performance of algorithm in real time driving.

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