Implementation of Autonomous Driving Vehicle at an Intersection with Traffic Light Recognition and Vehicle Controls

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Keywords: Autonomous Driving Vehicle, Crossing/Stop Decision, Traffic Light Recognition (TLR), Coordinates Map, Convolutional Neural Network (CNN).

Abstract: We implemented autonomous driving vehicle system at an intersection equipped with traffic lights. This system was consisted of a traffic light recognition, crossing/stop decision algorithm, vehicle localization, vehicle longitudinal/lateral control, and coordinate map generation. The traffic light recognition was implemented by using camera-based CNN data processing. The crossing/stop decision algorithm decides vehicle longitudinal control whether drive or not depending on recognized traffic light signal. The vehicle localization was implemented by using RTK GNSS and dead reckoning. The longitudinal control was designed by planned path data and the lateral control was designed by processed planned path data and traffic light position/signal recognition results. The overall vehicle control system was implemented based on an embedded control board. Coordinate map was made by saving vehicle's position data received from RTK GNSS. To evaluate the performance of proposed system, we remodeled a commercial vehicle into autonomous driving vehicle and drove the vehicle on our proving ground. Our own proving ground for the test vehicle driving performance was located in Ochang Campus, Chungbuk National University. As a result, the proposed vehicle successfully drove at intersection equipped with traffic lights with a maximum speed of 40 kph on a straight course and a maximum speed of 10 kph on a 90° corner course.

1 INTRODUCTION

As the fourth industrial revolution has progressed in recent years, research on autonomous driving vehicle system is actively under way. Autonomous driving vehicle system can be applied to various industrial fields such as drone, factory robot, etc. However, the autonomous driving vehicle system of the vehicle can bring societal advantages such as convenience, safety and economically efficiency of people. According to the Korea police DB in the TAAS(Road Traffic Authority, 2018), the number of traffic accidents in the intersection area for one year in 2017 is 102,354. The number of traffic accidents is a large proportion, accounting for 47.3% of 2016, 335 cases. Therefore, if an autonomous driving vehicle system that guarantees safety of vehicle operation is implemented at intersection, the proportion of traffic accidents can be greatly reduced.

The autonomous driving vehicle system is constructed by mimicking the driving method of the actual vehicle driver. The intelligent sensor is responsible for the driver's ability to distinguish objects around the car. Typical examples are Radar, Lidar, Camera and Ultrasonic sensor. The driver's driving control, such as Steering, Brake and Acceleration, is replaced by an electronically controlled way. And the brain responsible for the driver's judgment is replaced by a high-performance computing system.

Hardware systems that handle autonomous driving and judging have already had the capability to replace the usual driver's abilities. However, the vehicle sensor are not able to meet the driver's cognitive ability due to the physical limits of the sensing method and the misdetection problem in the poor driving environment. Radar sensors are capable of precise longitudinal distance measurements. But it

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Park, C. and Kee, S.
Implementation of Autonomous Driving Vehicle at an Intersection with Traffic Light Recognition and Vehicle Controls.
DOI: 10.5220/0007760905420549
In *Proceedings of the 5th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2019)*, pages 542-549
ISBN: 978-989-758-374-2

lack the ability to distinguish objects from lateral distance measurement (Reina et al., 2015). The Lidar has the advantage of being able to be used in both daytime and nighttime situations, but it lacks low resolution and mass production reliability verification (Lim, 2014). The camera can acquire a lot of information about the driving situation, but the image quality deteriorates seriously due to lighting change, weather change, and the like (Jo and Lee, 2015).

In this study, the autonomous driving vehicle system based on the traffic lights recognition was performed by using a monocular camera installed in front of the vehicle. Therefore, It is necessary to develop a TLR algorithm that can operate in a low-quality camera image environment.

TLR algorithms are divided into Non-Learning based algorithms and Learning-based algorithms. Non-learning based algorithms recognize traffic lights based on color data such as HSV or YCbCr (Jung and Kim, 2017). When the camera recognizes the traffic light, it captures a sky area that changes color sensitively according to time and weather. Therefore, In this paper, We implemented robust Learning-based algorithms(Website-WIKIPEDIA, 2019) for various environments. Also, as a feature of Autonomous vehicle, the algorithm requires a model capable of real-time processing, and details are described in '2. TRAFFIC LIGHT RECOGNITION ALGORITHM'.

In the field of the Vehicle Localization, There are various methods such as only GNSS, 3D Lidar with IMU (Heo and Park, 2016), Ultrasonic (Kim et al., 2007), Dead Reckoning (Jung, et al., 2012). 3D Lidar, IMU and Ultrasonic methods are a solution to solve the problem of cost and environmental constraints of GNSS. And guarantee higher performance when used with GNSS. In case of Dead Reckoning, reliability is lower than other methods. But real-time is guaranteed.

In this study, We implement Autonomous driving vehicle system in the area without GNSS obstruction. Therefore, We constructed the system using GNSS and to guarantee the real-time, Dead Reckoning is added. The detail are described in '3. VEHICLE LOCALIZATION'. Meanwhile, the generation of the vehicle driving path is also implemented using the GNSS method, and will be described in detail in '4. DRIVING PATH GENERATION USING COORDINATE MAP'.

The Vehicle Path Following is implemented by inputting longitudinal and lateral control values to the embedded control module equipped in the vehicle based on the generated driving path. At longitudinal and lateral control, there are various methods such as PID, Pure Pursuit, Stanley Control, Kinematic Control, LQR with FF Control, Preview Control (Snider, 2009). Each of the algorithms has a different advantages in various environment such as high speed situation, a low speed situation, a high curvature situation, and the like. In this paper, we use robust algorithms for low speed and high curvature conditions considering the characteristics of intersections. And detail are described in '5. VEHICLE CONTROL SYSTEM AND PATH FOLLOWING'.

The judgment of the driving state of the vehicle depends on the recognition result of the TLR. In particular, the yellow signal decision algorithm which has two states of stop and go is implemented by using the speed of vehicle, the distance between vehicle and stop line, the length of the intersection. The detail are described in '6. STOP/CROSSING DECISION ALGORITHM'.

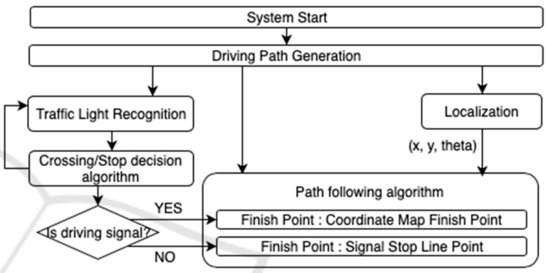

Figure 1: System block diagram summary.

In this paper, we used Hyundai Ioniq plug-in hybrid vehicle for implementing Autonomous Driving System based on vehicle. And the system is consisted of the TLR, the Vehicle Localization, the Driving Path Generation, the Path Following and the Decision of vehicle driving signal. (Figure. 1)

2 TRAFFIC LIGHT RECOGNITION ALGORITHM

In this paper, the TLR Algorithm is shown in Figure 2. It extracts the signal information from the front camera, extracts signal information using CNN model, detects proximity signal through size comparison, class integration for the same signal, and finally recognizes the final signal by extracting signal information based on the cumulative probability (Jang and Cho, 2017).

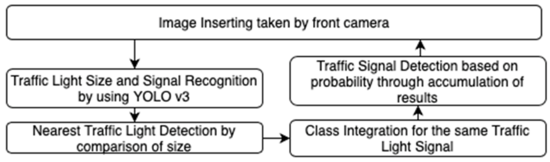

Figure 2: Traffic Light Recognition system block diagram.

2.1 Camera Calibration for TLR

The camera sensor is attached near the windshield at the front of the vehicle. The camera external parameter calibration is experimentally performed so that the traffic light area from the intersection entry area to the intersection passage area is included in the field of view of the camera. Also, As consider intersection entry speed of vehicle, traffic light detection should be performed before 85m from the intersection area. Therefore, 25.36° narrow angle lens is used to detect long-range traffic light to improve image resolution. And to shoot traffic lights in a variety of outdoor lighting conditions, The Camera is configured with a 1/1.8" sensor format and a 3.45x3.45um pixel size.

2.2 Classification Model

The recognition of the traffic lights in the autonomous driving vehicle system requires robust performance in the weather and lighting changing environment. Especially, in the backlight situation, the traffic light vanishing phenomenon is happened by sunlight.
In this environment, the algorithms need very high recognition performance and reliability in the weather and lighting changing environment.

In this study, we implemented a Deep Learning algorithm using a large amount of training data including general environment image data and poor environment image data. Also, the autonomous driving vehicle systems require real-time processing algorithms. The recently introduced YOLO V3(Joseph Redmon, Ali Farhadi, 2018) guarantees robust recognition and real-time in situations with complex backgrounds and external lighting changes. Therefore, we adopted it as a detecting model.

2.3 Training Data Configuration

Table 1: YOLO V3 Ground Truth Data Information.

Type	Block Type	Signal Type	Total
0	3 Signal block	Red	370
1		Yellow	242
2		Green	1119
3	4 Signal block	Red	4029
4		Yellow	96
5		Green	1914
6	4 Signal block	Left Arrow / Green	1101

The images of traffic light used in the training were taken while driving the vehicle. The images were taken on a clear day, cloudy day and rainy weather. The composition and number of the traffic light images used in the experiment are shown in Table 1 (Park and Kee, 2018).

Training data classes, written Block Type and Signal Type in Table 1, are divided into as many classes as possible for the same traffic light signal. And the ROI(region of interest) of the GT is constructed by multiplying 1.2 times to width of traffic light and multiplying 1.5 times to height of traffic light.

2.4 Training Data Extending

The basic principle of Deep Learning is to train the weights of neural networks according to training data and to derive desired results. Therefore, training using Deep Learning requires training data of various environments. If the environment of the training data is limited, the result will be reliable only in the trained environment.

YOLO V3, a Learning based algorithm, was implemented using the dedicated frame tool, Darknet (Website-Joseph Redmon, 2018). The frame tools provides a Data Augmentation (Salamon and Bello, 2016) methods that reinforces the kind of YOLO V3 input data. Data Augmentation methods modifies the hue, saturation and exposure of the input training image to create a new training image.

In this study, The Data Augmentation methods was optimized for TLR. One of the features of the TLR is that the position information of the signal can be used when determining the signal type. Therefore, in this study, we did not use only the flip option, which is a symmetric technique, among all Data Augmentation technologies that Darknet supports by default.

2.5 Traffic Light Signal Detection and Post Processing

The YOLO V3 algorithm applied to the TLR outputs the size, position and signal type information of the traffic lights. Generally, A large number of Traffic Lights with different sizes are detected in one image. Among the many Traffic Lights, what we need to detect is the nearest one. Therefore, by comparing the sizes, we decided what we have to recognition.

Refer to Table 1 and Figure 3. The Traffic Light Signal Information consists of 7 type. And, It is divided into block and signal type. The block means the number of signal ball. And the signal means color of ball. In this study, we have integrated the multiple same signals into represent one. For example, red signal of 3 signal block and red signal of 4 signal block is same.

Finally, to improve recognition rate, we accumulate recognized result. And as a final detection signal, we select the most frequent one among the accumulated data. If we accumulate a lot of many data, the TLR performance will be improved. However, It requires a large amount of system load.

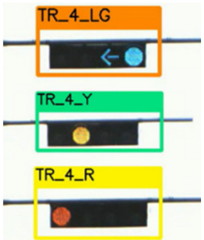

Figure 3: The result of TLR. The method of naming is TR_ [B]_[C]. TR mean Traffic Light Recognition. [B] mean the number of circle in Traffic Light. And [C] mean sign al of traffic light. (R : Red, LG : Left arrow and Green, Y : Yellow).

3 VEHICLE LOCALIZATION

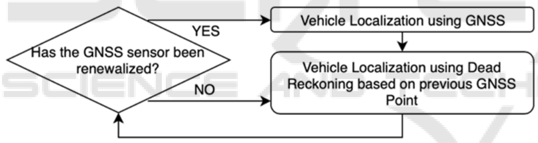

Figure 4: Vehicle Localization System Block Diagram.

In this paper, the vehicle localization is consisted as shown in Figure 4. This system simply implemented by using RTK GNSS (Website-WIKIPEDIA, 2019) and Dead Reckoning.

The GNSS sensor is attached to the vehicle and receives information of (x, y, theta). However, since it has a maximum error of 10m, RTK method that has a maximum error 10cm is used. The error is a range that can be used for vehicle localization. However, since the reception frequency is 1 to 5 Hz, real-time performance in the vehicle cannot be guaranteed. Therefore, the localization of the vehicle between the GNSS reception intervals is estimated using Dead Reckoning. Although the accuracy of the Dead Reckoning is lower than that of the RTK GNSS, it is implemented using a wheel encoder and a gyroscope that are guaranteed real-time. (Woo et al., 2009), (Langley, 1998)

3.1 Vehicle Localization using RTK GNSS

We use C94-M8P module to implement RTK GNSS. And RTK GNSS is implemented using NTRIP. Receive the GNSS correction signal of Korean Geographical Information Service through internet communication and calculate the exact position of GNSS sensor. The GNSS sensor is attached to the upper roof of the rear axle of the vehicle like Figure 5. The reception frequency setting and the NTRIP setting of the GNSS sensor were performed using U-CENTER software. In this study, we set the receive frequency to 5Hz.

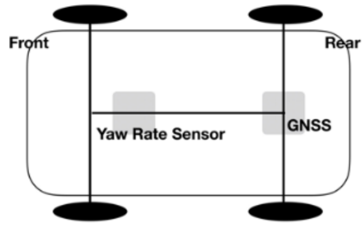

Figure 5: Attaching sensor for vehicle localization.

3.2 Vehicle Localization using Dead Reckoning

Dead Reckoning is implemented using the angular velocity and driving speed of vehicle output from the embedded control module equipped for autonomous vehicle. Implementation of the vehicle localization via Dead Reckoning follows the equations (1), (2) and (3).

$$\theta \approx \Delta\theta \times \Delta t \tag{1}$$

$$x_{new} = x_{old} \times \Delta c \times \cos(\theta) \tag{2}$$

$$y_{new} = y_{old} \times \Delta c \times \sin(\theta) \tag{3}$$

At equation (1), (2) and (3), θ means heading of vehicle. It is calculated using Yaw Rate Sensor value indicated in Figure 5. And Δc means the distance traveled of vehicle for a short time. (x_{old}, y_{old}) is the previous position of vehicle and (x_{new}, y_{new}) is the current position.

4 DRIVING PATH GENERATION USING COORDINATE MAP

The Driving Path is generated through a pre-made coordinate map. The coordinate map is composed of points from the beginning to the end of the vehicle to follow. Each point stores 7 kinds of information for vehicle control

1) Address of points
2) Longitude
3) Latitude
4) Longitudinal Target Speed of vehicle
5) Stop Point Latitude
6) Stop Point Longitude
7) Stop Point Address

The points shown in Figure 5 are created based on the GNSS sensor attachment point and uses the RTK GNSS. At this time, RTK GPS reception frequency is 1Hz and the interval between points is about 2.78m.

5 VEHICLE CONTROL SYSTEM AND PATH FOLLOWING

Figure 6: Hyundai Ioniq plug-in Hybrid used in the experiment.

This paper implemented the system based on real vehicle. The vehicle equipped with an embedded control module and front camera used in the experiment is shown in Figure 6. The vehicle control system is shown in Figure 7.

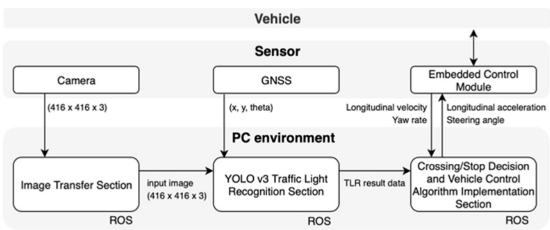

Figure 7: Vehicle Control System block diagram.

The embedded control module inputs the longitudinal acceleration and lateral steering angle of the vehicle. In this paper, the longitudinal control of the vehicle is implemented using the PD controller. (Bae, 2013) And the lateral control of the vehicle is performed using the Pure Pursuit controller. (Park and Kim, 2015)

In this paper, the longitudinal PD controller experimentally set the controller Gain to allow smooth speed rise and stop. In addition, the I component of the PID controller is not used because the steady-state error is not significant. As the lateral controller, Pure pursuit applied Look Ahead Point method similar to real driver was used. The calculation formula to get steering angle of vehicle using Pure Pursuit is shown at (4).

$$\delta = \tan^{-1}(k \times (2W_b Sin(\alpha)) / (v + 5)) \quad (4)$$

At equation (4), δ means steering angle of vehicle. k means hyper-parameter. W_b means wheel-base length of vehicle. α means an angle between a heading of vehicle and a Look Ahead Point. v means longitudinal speed of vehicle.

6 STOP/CROSSING DECISION ALGORITHM

The Stop/Crossing Decision Algorithm is an algorithm that judges the driving and stopping behaviour of the vehicle. And the system is summarized in Figure 8 as block diagram.

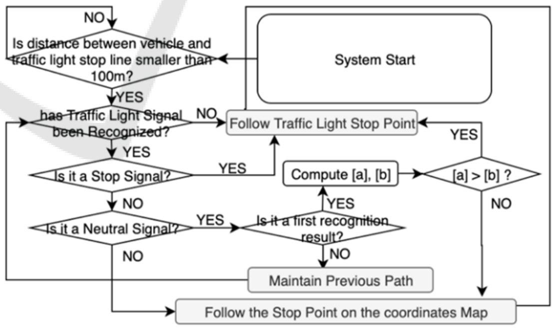

Figure 8: Decision algorithm block diagram. [a] is a result of adding (5) and (6). [b] is a result of (7).

The Stop/Crossing Decision Algorithm is implemented based on the recognized signal, the speed of the vehicle, the distance between the vehicle and the stop line and the distance of the intersection section. The recognized signal is finally output in three states of Driving, Neutral and Stop. And each means that the result of the TLR is green, yellow and red.

For the Neutral signals, the signal is determined by the speed of the vehicle and the distance between the stop line and the vehicle. If the sum of the traveling time (5) to the intersection passing time (6) is shorter than the holding time of neutral signal (7), this algorithm determines it as a Driving signal. If not, However, this algorithm determines it as a Stop signal.

In this paper, We implement this system at Autonomous Vehicle Proving Ground equipped with intersection located in Ochang campus, Chungbuk National University.(Figure 9) As constant variable, Therefore, we determines $d_{Intersection}$ as 7m,$v_{Intersection}$ as 10kph and $t_{NeutralTime}$ as 5 sec.

$$t_{StopLine} = (d_{StopLine}/v_{SignalDetection})\times 3/2 \qquad (5)$$

$$t_{Intersection} = (d_{Intersection}/v_{Intersection}) \qquad (6)$$

For the Driving signal, the vehicle follows the stop line of the traffic light. At this time, the longitudinal target velocity is linearly reduced to zero.

7 EXPERIMENTAL METHODS AND RESULT

This experiment is progressed in Autonomous Vehicle Proving Ground with the intersection equipped with traffic light located in Ochang campus, Chungbuk National University.(Figure 9)

Figure 9: Autonomous Vehicle Proving Ground with Inters ection equipped with Traffic Light.

This system was implemented with maximum 40kph in the straight section and maximum 10kph in the corner section. The performance of this system is shown in Table 2, 3, 4, 5 and Figure 10.

Table 2 shows the performance evaluation of the TLR algorithm. It defines a sequence as a distance of 85 m from a traffic light to a point passing through an intersection.

Table 3 and 4 shows the vehicle control performance for lane departure and stopping at stop point under real driving environment.

Table 5 shows the decision performance according to the Stop or Crossing in the yellow state.

Figure 10 is a longitudinal and lateral control performance graph. And This data was written as one second intervals. At this Figure, Lateral Distance Error means vertical distance error between the path heading and the vehicle.

Table 2: The result of the TLR. The confusion matrix is used for the performance evaluation, and it is defined as one sequence from the distance of 85m to the moment when the vehicle passes through the traffic lights (Park and Kee, 2018).

Type	Sequence	Result
Red / Yellow	30	30TP
Green	30	30TP
Green to Yellow	15	15TP
Red to Green	15	15TP
Recall, Precision		100%

Table 3: Vehicle Lateral Control Performance Result.

90° Corner section (kph)	Attempts	Success (In Lane)	Failure (Out Lane)
10	25	25	0
15	25	23	2
20	25	19	6
Straight section (kph)	Attempts	Success (In Lane)	Failure (Out Lane)
20	25	25	0
30	25	25	0
40	25	25	0

Table 4: Vehicle Longitudinal Control Performance Result. It indicates the distance error between the stop line and the vehicle when the vehicle is stopped.

Attempts	Result		Stop Point Distance Error (m)		
25	Over line	2	0.012	0.021	0.017
	In line	23	0.011	0.108	0.032

Table 5: The result of intersection driving of autonomous vehicle at Neutral Signal Decision State.

Straight Course (kph)	90° Curved Course (kph)	Neutral Signal Decision Result	Success	Failure
20	10	Stop	15	0
		Crossing	15	0
30		Stop	15	0
		Crossing	15	0
40		Stop	15	0
		Crossing	15	0

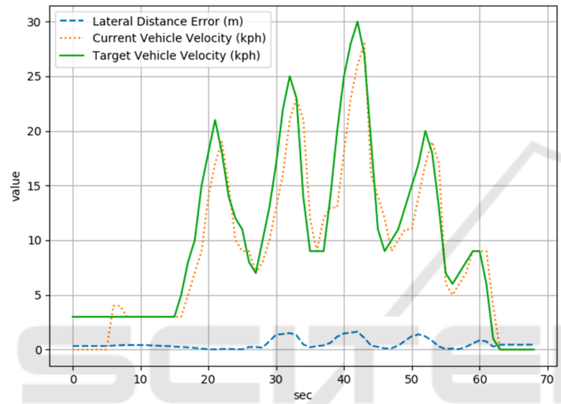

Figure 10: The result of vehicle's lateral, longitudinal control according to vehicle's velocity. Curved sections mean 90° corner course.

8 CONCLUSIONS

In this paper, the autonomous driving vehicle system was implemented using real vehicle equipped with intelligent sensor and embedded control module at intersection area equipped with traffic light. The study was conducted on three areas: Traffic Light Recognition, judgment of behavior of vehicle based on recognized signals and vehicle control.

The system was successfully implemented at Autonomous Vehicle Proving Ground located in Ochang campus, Chungbuk National University.

At traffic light recognition and signal judgment, the behavior of vehicle recognized as yellow signal was mainly studied. And this content was written at '6. STOP/CROSSING JUDGMENT ALGORITHM'. In this study, the holding time of the yellow signal from traffic light was fixed as 5 sec. To implement robust judgment algorithm, However, the systems have to receive accurate holding time. For example, if we use V2X methods, we can get the accurate holding time to maintaining yellow signal.

At vehicle control, we implemented this system using localization of vehicle and longitudinal/lateral control. At part of localization, by using both RTK GNSS and Dead Reckoning, '3. VEHICLE LOCALIZATION' was consisted. However, in this study, lateral control was not stable due to GNSS heading error which randomly changed maximally up to 5°. Therefore, it is necessary to compensate the problems by a technique such as a Kalman filter. Also, it is difficult to getting trusting data from GNSS located between high-rise buildings. Also, In case of Dead Reckoning, Because it has low reliability compared to GNSS, it is used as complementary algorithm of GNSS. However, if it is implemented through a high-quality algorithm, the performance of the localization will improve.

At control of vehicle, PD controller is used to longitudinal control. And Pure Pursuit controller is used to lateral control. More details are covered in '5. VEHICLE CONTROL SYSTEM AND PATH FOLLOW'. In this study, the PD controller of longitudinal control is implemented in the low speed situation. Therefore, the stopping and running performance cannot be relied on in high speed situation. Actually, in real road, there are many challenging environments, such as inclement weather, high curvature road, and so on. And to comfortable ride, accurate control is necessary. Also, the Pure Pursuit controller applied to lateral control is not stable for all environment. If you want, advanced control algorithm, such as Kinematic control, LQR with FF control, Preview control, MPC (Lee and Yi, 2015), and so on, is needed.

As a result of this study, the conclusions could be summarized that it is experimentally proved that it is possible to partially implement an autonomous driving system using a commercial vehicle through public recognition algorithm and control algorithm with proposed stop/crossing decision algorithm.

ACKNOWLEDGEMENTS

This work was supported by Institute for Information & communications Technology Planning and Evaluation (IITP) grant funded by the Korea government (MSIT) (No. R7117-16-0164, Development of wide area driving environment awareness and cooperative driving technology which are based on V2X wireless communication).

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