Detection method of Blind Spots Region on Merging Section Using V2X Communication of Autonomous Vehicles

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***Abstract*— In this study, we propose a method for detecting blind spots in merging sections of roads using V2X (Vehicle-to- Everything) communication to enhance the safety and reliability of autonomous vehicles. While autonomous vehicles can detect surrounding objects through object perception technologies, there are situations where blind spots can occur in merging sections of roads. These blind spots can lead to uncertainties in predicting the movements of surrounding vehicles and accurately determining the autonomous vehicle's position. We utilize V2X communication to exchange object information detected by the road infrastructure. The autonomous vehicle receives information such as the positions, velocities, and directions of surrounding objects and uses HD map information to calibrate the location of the object. This solves the position error problem of surrounding objects. By doing so, we can detect blind spots in merging sections of roads and predict potential collision points with other vehicles. This enables the autonomous vehicle to respond quickly and effectively. To validate the proposed method, we conducted experiments using real-world road scenarios. The results demonstrate that blind spot detection using V2X communication enables safe autonomous driving. This method contributes to improving the safety of autonomous vehicles and enhances overall traffic safety.**

Keywords—Connected vehicle, Autonomous driving, Blind spot detection, V2X communication, road infrastructure

I. INTRODUCTION

Currently, the automotive industry is undergoing very rapid change, centered on the advancement of autonomous vehicle technology. Autonomous vehicles break away from the existing driver-centered driving method and drive and control driving on their own through sensors and algorithms. It is expected that this will increase the safety and efficiency of car driving, and play a major role in reducing traffic congestion and the possibility of traffic accidents. However, autonomous vehicles still have the possibility of road safety accidents. Since autonomous vehicles must drive in various environments and situations, the performance of autonomous driving systems is very important. In particular, real-time communication between autonomous vehicles and road infrastructure is essential. To this end, a V2X (Vehicle-to-Everything) communication system has been proposed.

The V2X communication system supports the driving of autonomous vehicles [1-3] by exchanging information such as real-time traffic information and vehicle location, speed, and acceleration through communication between vehicles and between vehicles and infrastructure. Through this, autonomous vehicles can prevent collisions with other vehicles and perform efficient driving by predicting traffic congestion. Therefore, V2X communication systems can play a major role in preventing problems such as vehicle-to-vehicle collisions and traffic congestion, and improving road safety and efficiency.

Existing research on blind spot detection methods [4-6] for self-driving cars has already been conducted in various ways. Representative examples include methods for detecting blind spots using various sensors such as cameras, LiDAR, ultrasonic sensors, and radar. However, these methods still have limitations. First of all, the camera-based blind spot detection method is greatly affected by environmental factors such as weather and lighting. In particular, in weather such as rain or fog, the screen is blurred or noise is generated, resulting in poor detection accuracy. LiDAR-based methods can detect blind spots relatively accurately, but are very expensive. Also, while radar-based methods are generally good at detecting long distances, they have limitations in detecting stationary objects. In addition, it is very difficult to detect vehicles approaching to merge in the merging section as they are covered by road structures. In order to supplement the limitations of the existing blind spot detection methods for self-driving cars mentioned above, studies using self-driving V2X systems are being conducted recently.

Considering these backgrounds and problems, this paper proposes a method for detecting objects located in blind spots in the merging section by collecting object information on the road through V2X communication with the road infrastructure [7]. In the road infrastructure, road conditions are detected using sensors such as cameras, radar, and lidar, and this information is transmitted to autonomous vehicles through V2X (Vehicle to Everything) communication. Through this, the self-driving car can use the information transmitted from the road infrastructure to identify information on surrounding

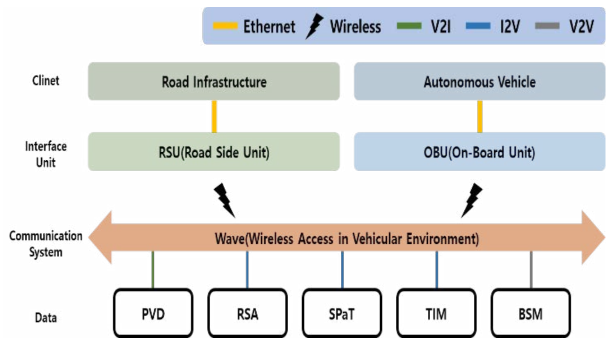


Figure 1. Overview of the interface between road infrastructure and vehicles

objects. However, since the object information detected in the actual infrastructure contains an error of up to 3 m, HD map information is used to supplement the corresponding part[8]. It is possible to compensate for the positional error of the collected object and to predict the movement path of the object to determine whether it collides with an autonomous vehicle. Depending on whether or not there is a collision, the self-driving vehicle can change the control value, and safe autonomous driving is possible.

II. Object Detection Using V2X System

A. *Interface of Vehicle-to-Infrastructure*

The road infrastructure system transmits emergency situation information through wireless communication between vehicles and provides real-time traffic information in conjunction with an intelligent traffic system. Autonomous vehicles receive data such as PVD (Probe Vehicle Data), RSA (Road Side Alert), SPaT (Signal Phase and Timing), TIM (Traveler Information Message), and BSM (Basic Safety Message) through infrastructure built on roads. Among the data that can be collected from the road infrastructure, RSA data includes road hazard warnings and event information, and delivers information such as vehicles, falling objects, pedestrians, and reverse driving. Therefore, we utilize RSA data to detect objects around the vehicle.

The interface between road infrastructure and autonomous vehicles is shown in figure 1. Road infrastructure and autonomous vehicles transmit and receive data using V2X communication based on WAVE (Wireless Access in Vehicular Environment). Data detected by the road infrastructure is transmitted through RSU (Road Side Unit), and the autonomous vehicle receives data through OBU (On-Board Unit) equipped in the vehicle. The data interface with OBU can receive data using ethernet-based TCP/IP communication, and to receive RSA data, the data was collected by configuring a message as shown in Table 1.

Table 1. Details of object data message structure of infrastructure

Name	Type	Unit	Description
Timestamp	Time	-	Transmission time
Num of object	Unit8	[0, 255]	Object number
Event type	Unit32[]	[1~65535]	Object type
ObjectID	Uint16[]	-	Object ID
Longitude	Float64[]	deg	Object longitude
Latitude	Float64[]	deg	Object latitude
Heading	Uint16[]	deg	Object heading
Speed	Uint16[]	m/s	Object speed

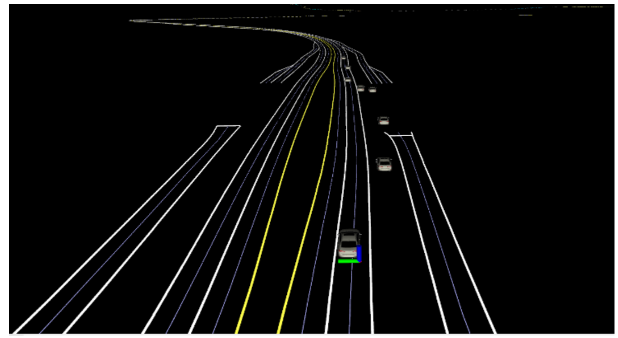


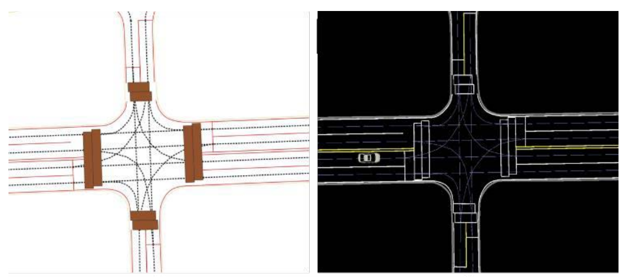
Figure 2. Object visualization image

When data is collected, the location information (Longitude, Latitude) of the object detected by the road infrastructure has the WGS coordinate system. We converted from the WGS coordinate system. We converted from the WGS coordinate system to the UTM coordinate system to utilize the location information of the object. Figure 2 is the result of converting the coordinate system of the object location information received from the road infrastructure and visualizing it on the HD map.

Referring to the specifications of detectors installed in road infrastructure, the accuracy of object detection includes an error of up to 3 m. Therefore, as a result of collecting the location information, it can be confirmed that some objects in figure 2 are displayed on a location other than the road.

B. *Blind spot detection through position calibration*

Objects recognized by the infrastructure system built on actual roads deliver location information values that include errors. This can be fatal in the control part of autonomous vehicles. We used the HD map to calibrate the error value. HD Map is a 3D representation of road network information (nodes, links), road section information (tunnels, bridges, etc.), sign information (safety signs, lanes, crosswalks, etc.), facility



(a) (b)

Figure 3. HD map image, (a) HD map viewer image, (b) autonomous driving system ui)

Table 2. HD map main component layer

Layer	Description	Type
A1_NODE	Connecting points of driving link	Point
A2_LINK	Virtual driving path line	Line
A3_DRIVEWAY SECTION	Roads such as tunnels and bridges	Plane
B1_SAFETYSIGN	Common attribute values for safety signs	Point
B2_SURFACELINEMA RKER	Line-shaped Road markings	Line
B3_SURFACE MARKER	Plane-shaped Road markings	Plane
C1_TRAFFICLIGHT	Traffic light information	Point
C4_SPEEDBUMP	Speedbump information	Plane
C6_POSTPOINT	Post point information	Point

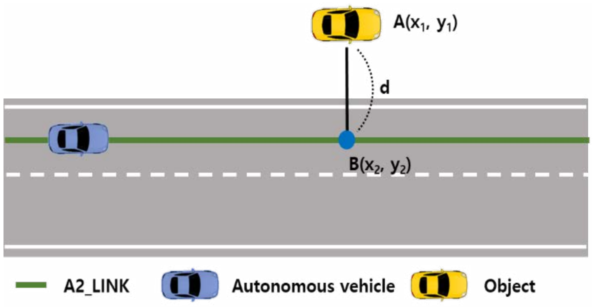


Figure 4. Calibration of object position

information (traffic lights, safety facilities, etc.) and has a precision of about 0.25 m. The HD map is composed as shown in figure 3, and the main layers are shown in Table 2.

We used the driving route link (A2_LINK) among the multiple layers of the HD map to calibrate the vehicle's location data. A2_LINK is a green line in figure 4, which means a virtual path line (linker) that an autonomous vehicle can refer to while driving, and linker (L) is a set of location points (p) on the road.

$$p = \{x_i, y_{i,}, z_i\}, \mathrm{L} = \{p_1, p_2, \cdots, p_n\} \tag{1}$$

For the position calibration method of object data, we search for the nearest linker based on the position data of the object. The distance from the object to the linker (d) means the distance to a point perpendicular to the linker when a line from the object's position to the linker is connected. The procedure for calculating the position of the object (A), the point where the object is perpendicular to the linker (B), and the distance between the object and the linker (d) is as follows. First, two arbitrary location points (p_{r1}, p_{r2}) of the linker are extracted.

$$p_{r1} = \{x_{r1}, y_{r1}, z_{r1}\},\ p_{r2} = \{x_{r2}, y_{r2}, z_{r2}\} \tag{2}$$

Calculate the linear equation (equation 3) of the linker using the two location points (p_{r1}, p_{r2}). The location point includes height information (z), but the corresponding value is not used.

$$ax + by + c = 0\ (a \neq 0, b \neq 0) \tag{3}$$

$$a = (\,y_{r2} - \ y_{r1})\ /\ (x_{r2} - \ x_{r1}) \tag{4}$$

$$b = \ -1,\ c = y_{r1} - \ ax_{r1} \tag{5}$$

As with the linker, it calculates a straight line ($\overline{AB}$) between the position of the object (A) and the point where the object is perpendicular to the linker (B).

$$y - y_1 = \frac{y_2 - y_1}{x_2 - x_1}(x - \ x_1) \tag{6}$$

Since the straight line ($\overline{AB}$) and the linker's straight line (ax+by+c=0) are perpendicular to each other, the product of the slopes of the two straight lines has -1.

$$-\frac{a}{b} \times \ \frac{y_2 - y_1}{x_2 - x_1} \ = \ -1 \tag{7}$$

$$a(y_2 - y_1) = \ b(x_2 - \ x_1) \tag{8}$$

Since the length of the straight line ($\overline{AB}$) and the distance (d) between the object and the linker have the same value, the value of d can be derived by calculating the length of the straight line ($\overline{AB}$). The length of a straight line ($\overline{AB}$) was calculated using the distance equation between two points.

$$\overline{AB} = \sqrt{(x_2 - x_1)^2 - \ (y_2 - y_1)^2} \tag{9}$$

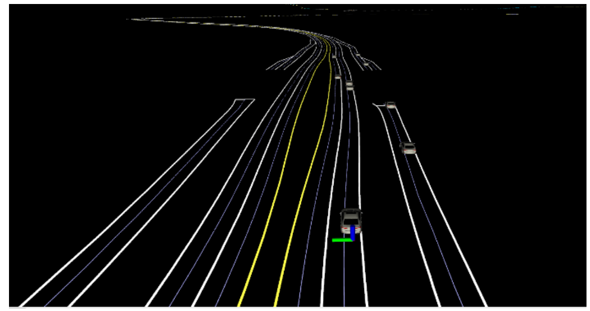


Figure 5. Result image of object position calibration

Applying the previously arranged formulas to equation 9, the distance (d) between the object and the linker can be calculated as follows.

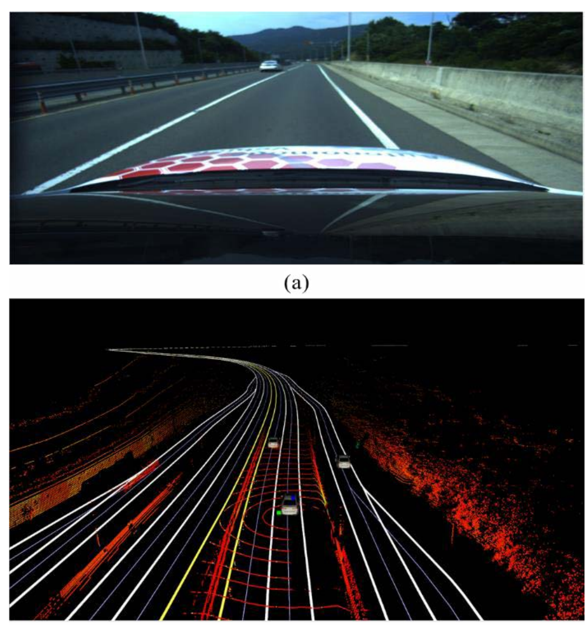
$$d \ = \ |ax_1 + by_1 + c|\ /\ \sqrt{a^2 + \ b^2} \tag{10}$$

Based on the object, the distance (d) with several linkers is calculated, and the linker with the minimum is detected. Then, the location of the point (B) perpendicular to the linker is extracted.

$$x_2 \ = \ (x_1 + ay_1 - ac)\ /\ (a^2 + \ b^2) \tag{11}$$

$$y_2 \ = \ ax_2 + c \tag{12}$$

The position of the object was calibrated by calculating the minimum distance between the object and the linker and calculating the position of the point perpendicular to the nearest linker. In some road sections (merging roads, diverging roads, etc.) where the structural form of the road is different, it is easy to distinguish the speed or height value of the vehicle, so the correction was performed in consideration of the speed and direction of the object in the corresponding area. The result of correcting the object position is shown in figure 5, and figure 6 is the result of recognizing objects located in the blind spot area that the self-driving vehicle cannot recognize with the sensor in sections such as junctions through object position correction.



(a)

(b)

Figure 6. Result image of blind spot detection in merging section, (a) camera image, (b) proposed method)

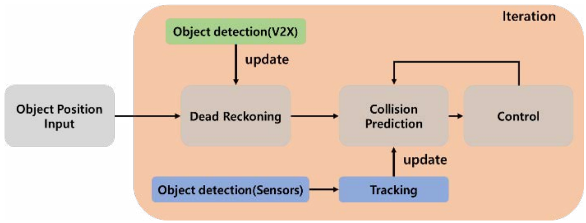


Figure 7. Collision prediction flowchart

III. Collision Prediction

An autonomous vehicle can receive information about objects detected by the infrastructure through V2X communication and detect objects located in blind spots that are difficult to detect with sensors in sections such as merging sections. In this chapter, we propose a method to calculate the expected point of collision with a driving autonomous vehicle and the time until the collision by utilizing the detected object 0information.

Figure 7 shows a flowchart for collision prediction. First, the object recognition values described in the previous chapter are set as the initial input. Then, we apply the dead reckoning method, which calculates the position through a simple physics formula, to estimate the moving position of the object and proceed with collision prediction. During the dead reckoning process, if an object recognition value is received from the infrastructure, it is updated to the corresponding location, and if an object is recognized by the sensor installed on the autonomous vehicle, the collision prediction is performed using the sensor measurement value. This is because the sensor recognition of autonomous vehicles is performed at a closer distance and has higher accuracy.

A. Prediction of vehicle behavior

Dead reckoning is a technique for estimating the next state in the absence of a network or signal. Road infrastructure transmits object information at a frequency of about 10 Hz. However, delays can occur due to environmental factors and communication load. On the tested roads, vehicles are driving at speeds above 60 km/h, so missing some data can become a risk factor.

To apply the dead reckoning technique, we predicted the path that the object will driving. To calibrate the position of the object, we used the driving path link (A2_LINK), which is a virtual route line that the vehicle can refer to while driving. Therefore, it is very likely that the object will move along this path, so we use A2_LINK to generate an estimated path for the object. Figure 8 shows the result of the predicted path of the object.

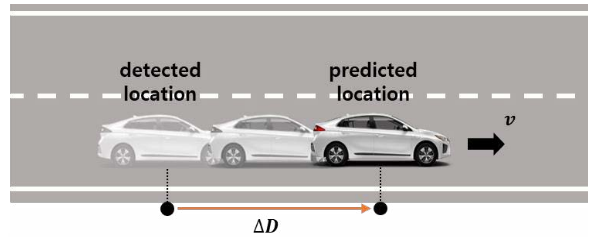


Figure 9. Dead reckoning technique schematic diagram

In this paper, the expected moving distance (ΔD) of an object is calculated using dead reckoning[9].

$$\Delta D = v \times \Delta t \tag{13}$$

The predicted distance drived (ΔD) is the distance between the detected object's current location (detected location) and the predicted location drived by a certain amount of time at the object's speed. The velocity (v) of the object is the value of the object's velocity provided by the infrastructure through the message defined in Table 1, and the time (Δt) is set to 0.05 s. Therefore, dead reckoning can update the expected movement information of the object at an interval of 0.05 s and guess the location of the object. For example, when the object is driving at 60 km/h, it moves 0.83 meters per 0.05 seconds. We can estimate the object's position by moving the object 0.83 meters every 0.05 seconds along A2_LINK.

B. Collision prediction

As an object's position is updated, its predicted path is also updated. We can use the paths of the objects to calculate the predicted collision points. In the case of the merging section, since it is a section where two roads merge, a collision point is necessarily generated, and the section means the point where the expected paths of the objects overlap.

Figure 10 shows the result of simulating dead reckoning along the vehicle's predicted path without updating the object's position. The red circles along the predicted path are the result of detecting and marking potential collision points. The risk of collision can be predicted by calculating the time to collision (TTC) of each vehicle to the predicted point of collision based on the predicted point of collision[10].

$$TTC = d(t) \,/\, v(t) \tag{14}$$

In Equations 14, d(t) means the distance between the target vehicle and the expected point of collision when the current time is t, and v(t) means the speed of the target vehicle. A collision can be predicted by comparing the TTC values of the driving vehicle and the approaching vehicle.

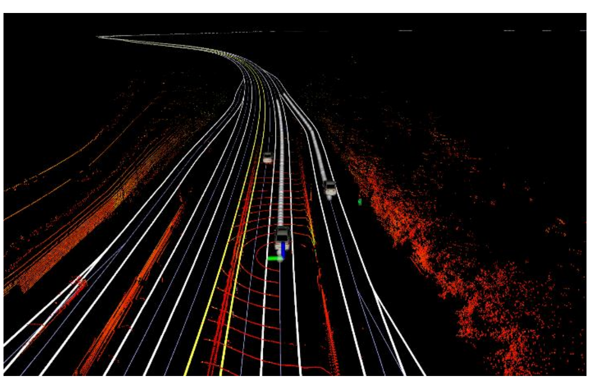


Figure 8. Image of driving path prediction result

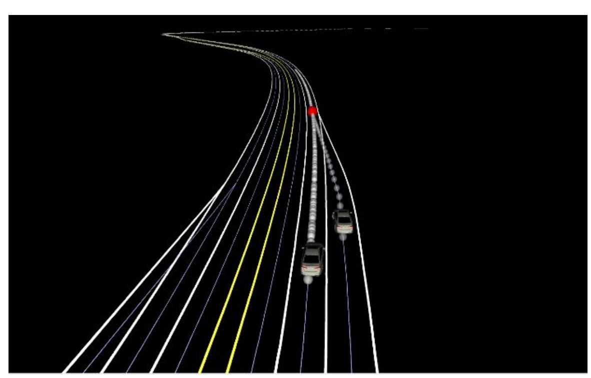


Figure 10. Detection of predicted collision points

IV. Experiments

A. Environments

To evaluate the method proposed in this paper, we collected and tested the infrastructure information on real roads, and the information was collected at Technopolis-road in Daegu, Korea. Technopolis-road is an infrastructure-based environment consisting of 2.4 kilometers of urban roads and 12.9 kilometers of highways for autonomous driving demonstration, with RSUs, object detectors, pedestrian detectors, positioning correction base stations and signal controllers. In addition, the V2X communication system for delivering information is designed to meet the SAE J2735 data exchange standard. We utilized the information of the object detector among the built infrastructure to collect the information of the object, and the location of the built object detector is shown in Figure 11.

The autonomous vehicle is a Hyundai Ioniq EV equipped with camera, lidar, radar, GPS, OBU, main PC for judgment/control, and sub PC for perception, as shown in Figure 12. The autonomous driving system is designed in Ubuntu, Linux environment, and includes perception algorithms using sensors such as camera and lidar, and control algorithms such as LKS (Lane Keeping System), AEB (Auto Emergency Braking), and ACC (Advanced Cruise Control). It also receives information from the infrastructure through TCP/IP communication with the OBU.

B. Experimental result

Two of the three object detectors deployed on the road contain data from the merging section. We tested the merging section for object detection and collision prediction in the blind spot area, and verified its performance by comparing it

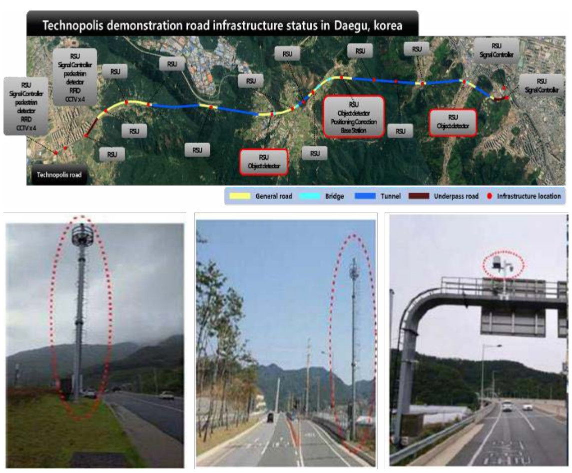


Figure 11. Infrastructure configuration and object detector images

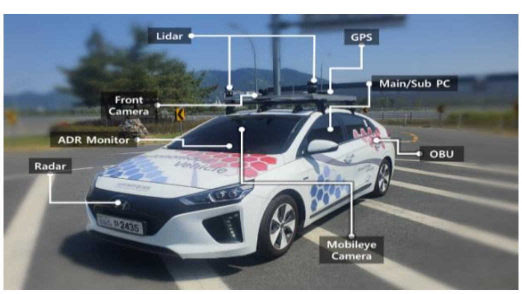
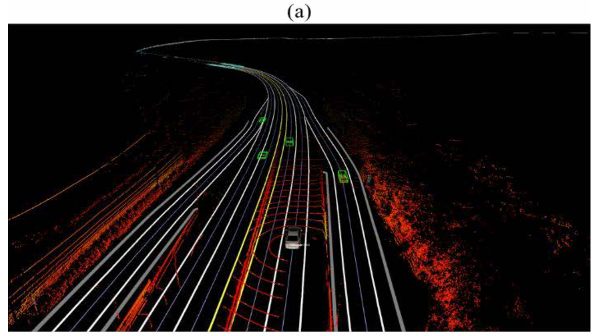
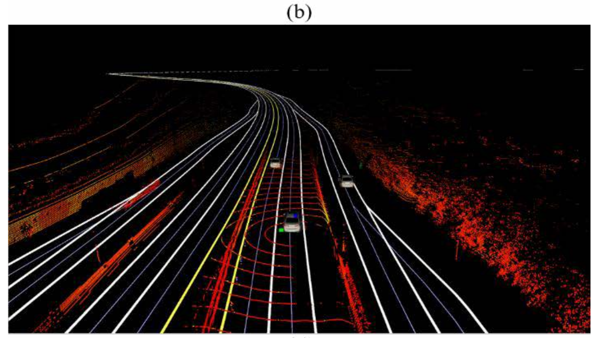


Figure 12. Autonomous vehicle

(a)



(b)



(c)

Figure 13. Result of object detection on merging section 1. (a) camera-based, (b) lidar-based, (c) proposed method

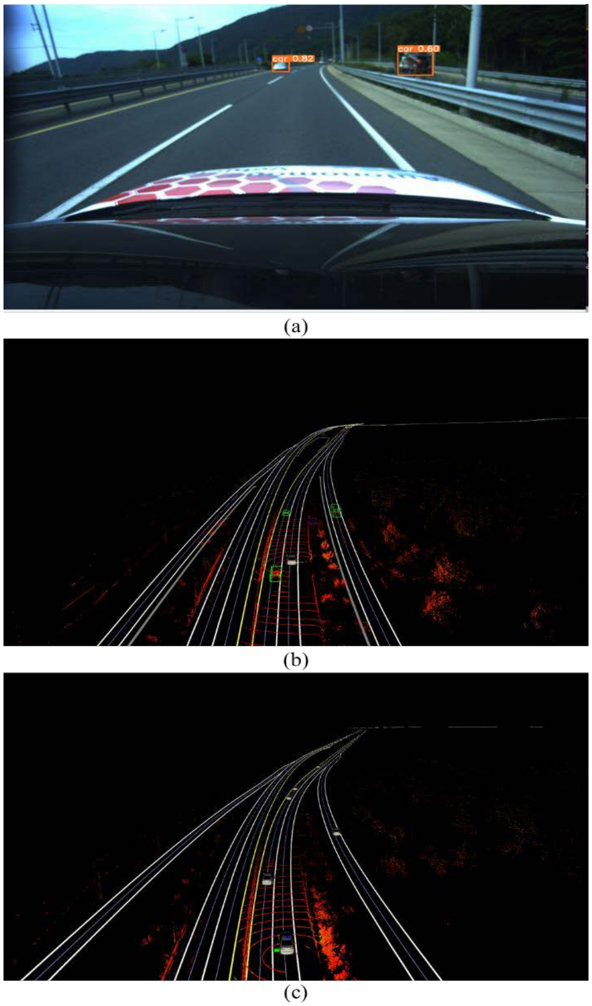
with the results of object detection using camera and lidar sensors. The test was evaluated by simulating the same data, and the comparison group was compared using an open source that users can easily access. The camera used yolo_v5[11], and the lidar used autoware AI's lidar detection algorithm[12].

Table 3. Distance to collision position according to object detection

Scenario	Distance to Collision position (m)					
	Camera-based		Lidar-based		Proposed method	
	ego	target	ego	target	ego	target
1	227.1	192.45	235.15	212.87	280.81	265.07
2	265.23	263.82	326.87	297.66	387.23	330.11

Table 4. TTC at the time of object detection

Scenario	TTC (s)		
	Camera-based	Lidar-based	Proposed method
1	13.381	13.464	15.988
2	13.785	16.015	18.914



(a) (b) (c)

Figure 14. Result of object detection on merging section 2. (a) camera-based, (b) lidar-based, (c) proposed method

The proposed method enables the detection of objects in areas that cannot be detected by sensors, and it is easy for autonomous vehicles to react to collisions because they can be detected at a distance from the expected collision point.

Since the object detector's object detection accuracy in the actual infrastructure cannot be verified, the proposed method enables the initial response of the autonomous vehicle and subsequent safe control through the sensor's detection results.

V. CONCLUSION

In this paper, we proposed a method to receive object information on the road using V2X communication and calculate the expected path of the object to estimate the expected collision point. As a result of experiments using infrastructure data of real roads, we were able to detect objects before the sensors of autonomous vehicles at points where collisions are expected, such as merging sections. Furthermore, we calculated the time-to-collision (TTC) to the collision point based on the detected object information. The proposed method confirms that it is possible to detect objects faster than sensors at points where collisions are expected, such as merging sections, and this enables actions such as performing initial control of the approaching vehicle. These initial controls can allow the autonomous vehicle to take actions such as slowing down to prevent a collision or minimize the risk of a collision.

In future work, we will conduct experiments on more diverse road conditions and object types to validate the performance of the proposed method. In addition, we hope to improve the safety of autonomous vehicles and the efficiency of the road environment by improving the efficiency and reliability of V2X communication and considering the applicability in real road environments.

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