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Data Fusion Driven Lane-level Precision Data Transmission for V2X Road Applications

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***Abstract*—Inter-vehicle communication is being developed continuously in order to accomplish a better driving experience. Through the exchange of information between vehicles and Road Side Unit (RSU), number of accidents can be reduced by notifying the driver through the facts obtained. In general, broadcast information for vehicles is sent in an ad hoc manner. However, unfiltered information may be useless and wasted for most vehicles. Thus, a raised question is whether precise information can be delivered only to the target vehicles without interfering with other non-target vehicles. A computer vision (CV) and sensor fusion-based transmission system are exchanged by RSU and Vehicle On-board Unit (OBU) is developed to attain this objective. In order to correctly transmit the specific information to the target vehicles, we propose a data fusion driven lane-level precision data transmission system that utilizes three kinds of sensory inputs: Road Side Camera (RSC), GPS, and magnetometer. By combining common features from these sensory inputs, our system is able to select the receiver of specific information on the road. Our system focuses on the scenario where a message can be transmitted to the target vehicles located in a certain lane. The experimental evaluation shows a recognition rate of 87.34% and the generated messages have a total delay less than 72 ms.**

***Index Terms*—alert message, data fusion, inter-vehicle-communication, V2X communication**

I. INTRODUCTION

The impressive growth of Internet of Things (IoT) has an impact on the smart city that consists of robust infrastructure, intelligent data communication, and system control [1], [2]. To establish a more digital and connected society, the availability of Intelligent Transport System (ITS) becomes vital [3]. ITS aims to improve the traffic efficiency, decrease traffic congestion, and enhance driver's experience. Since 5G provides faster network connection and lower latency, ITS can enable an inter-vehicle communication which allows the driver to be more aware of their surroundings. Therefore, it can also enhance a safe and improved driving system.

Inter-vehicle communications such as V2V/V2X allow vehicles to communicate with the neighbor vehicles and the RSU in an ad hoc manner [4], [5]. The interchange information usually consists of vehicle's status such as speed, location and direction of travel. These data exchanges can help to avoid a collision by sending a warning message to alert the driver [6], [7]. A more advanced autonomous driving system can even stop the vehicle directly.

In this work, we conduct a scenario where the vehicles communicate with RSU via V2X communications to get their surrounding vehicle/road/traffic information. Although this current information exchange system has been adequately good, the information is frequently undelivered to the suitable target. Combining the Computer Vision (CV) technology with V2X communication, the proposed system can deliver road information to the target vehicles in a certain lane by integrating the data from RSC and vehicles.

RSC is equipped with three sensors which are camera, GPS, and magnetometer, while vehicle is equipped with a GPS sensor. Thus, if any critical information is discovered, this information is delivered to the target vehicle directly via V2X communications. In addition, our proposed idea also improves the quality of delivery critical information in terms of positioning system. Since in this particular issue, GPS sensor's error rate could reach up to ten meters [8].

Fig. 1 shows the scenario where the proposed fusion model is performed in Mobile Edge Computing (MEC) Server. Assuming that there is pothole in the upper lane, a danger message will be sent to the vehicles on the upper lane, while a caution message will be sent to the surrounding vehicles (e.g. on second lane). That means the data transmission process should be effectively controlled up to lane level.

The technical novelties and contributions of this paper are as follows.

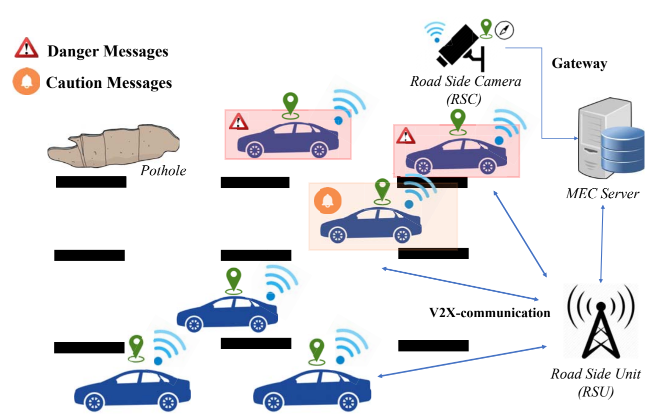

Fig. 1: Lane-level data dissemination scenario.

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1) Propose a new data fusion method called lane-level precision data transmission infrastructure which combines CV and V2X communication technology.
2) Attain an identity-awareness in V2X communication using data fusion technology.
3) Enhance the vehicle's location precision on autonomous vehicles, with our technique, 80% positioning accuracy of vehicle is improved to lane level.
4) Improve a better driving experience by increasing the accuracy of vehicle positioning and critical information delivery in order to intensify vehicle's safety.

The rest of this paper is organized as follows. Section II reviews related works. Section III discusses our proposed system model and design. Performance evaluation results are shown in Section IV. Finally, Section V gives conclusions and future works.

II. RELATED WORKS

A lot of works have developed V2V/V2X-assisted autonomous driving applications. In [9], an autonomous decision making system with a lane change maneuver algorithm is proposed. The system is in charge of finding the available lane and is able to control the vehicle to position itself in a certain gap on the target lane. In [10], a particle filter based on V2V communications is proposed to improve localization results of vehicles. However, this proposed solution highly depends on network quality; therefore, it is not suitable for cases with unstable network conditions. References [11], [12], [13] utilize smartphone sensors to reach lane-level localization on highways based on driving conditions. However, these works do not consider how to deliver critical information via V2X communications, such as alerting drivers to avoid car accidents, and do not consider how to apply CV to find high level information, such as potential emergencies.

On the other hand, CV has made significant progress recently. Convolutional neural networks [14], [15], [16] have been proven to be successful for image recognition and classification. As a convenient tool, You Only Look Once (YOLO) [17], [18] is able to detect thousands of objects from an image. A vision assisted positioning approach is proposed in [19]. Data fusion between V2V/V2X communications and CV for augmenting surrounding information is proposed in [20]; the result shows an augmented reality (AR) so the driver can visually see the driving status of its surrounding vehicles via V2V communications. Another application of data fusion is implemented in [21], [22] for drone views.

Despite these progresses, a lane level transmission filter is desirable to reduce irrelevant information transmission towards non-target vehicles. To our best knowledge, we are the first to fuse images from RSC, GPS, and magnetometer sensors data via V2X communications to attain lane-scale precision data transmission. Herein, we will use CV to extract high-level features for data fusion, lane mapping, and potential danger events that need to be alerted to drivers.

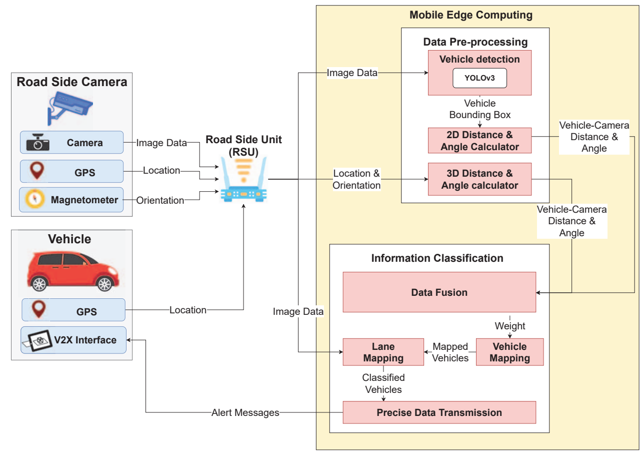


Fig. 2: System model of data fusion driven lane-level precision data transmission.

III. DATA FUSION DRIVEN LANE-LEVEL PRECISION DATA TRANSMISSION

Fig. 2 shows the proposed system model for data fusion driven lane-level precision data transmission. A RSC continuously captures videos and sensing data. The series of images and camera orientation are sent to MEC server to be processed. Each vehicle has an embedded on-board units (OBU) that connects to a GPS and a C-V2X transceiver. The GPS data are also transmitted to MEC server. In case of any critical information is discovered, MEC server shall find out the target vehicles by our proposed approach, and send the alert to target vehicles.

The videos transmitted to the MEC server are processed by YOLO [17] in order to identify the vehicles. On the other hand, based on GPS data sent by the RSC and vehicles, we can obtain the distances between RSC and vehicles. In addition, based on the orientation of RSC (obtained by the magnetometer sensor equipped on RSC), we can get the angle values between RSC and the vehicles. The next challenge is how to find out the target vehicles.

Assuming there are several vehicles $V^t = \{v_1^t, v_2^t, ..., v_n^t\}$ captured by RSC. Periodically, each $v_i^t, i \in \{1, 2, 3, ..., n\}$ will transmit its position to the MEC server on RSU for processing every time t. $B^t = \{b_1^t, b_2^t, ..., b_o^t\}$ are messages sent by the vehicles during a certain time t. Then, our proposed approach will find out which messages are transmitted by which vehicles, and get a set M:

$$M^t = \left\{(v_i^t, b_j^t) \mid v_i^t \in V^t \ and \ b_j^t \in B^t\right\} \tag{1}$$

There is a Lane Mapping module in the MEC server. This module maps the vehicles into the certain lane l, and the lanes L from the view of RSC can be denoted as follows:

$$L = \{l_1, l_2, ..., l_k\}, \tag{2}$$

Furthermore, a Precise Data Transmission module will find out the target vehicles based on M^t, L, and V^t. Each block diagram in Fig. 2 is demonstrated as follows:

A. Data Pre-processing

In this block, the data from camera, GPS, and magnetometer sensors are extracted to get the common features. In this work, distance and angle features are considered.

1) 2D Distance and Angle Calculator Module: To identify the vehicles in the image, we use YOLO [17]. The main purpose of this module is to get the list of detected vehicles in the frame and the angle between RSC to each vehicle on the road. Assume the RSC has 35 mm as a digital camera's full frame format with a specific focal length [23]. Once the image has been captured and analyzed using YOLO, vehicle's distance from RSC can be estimated using the height of object by combination of the Lens equation and Magnification Equation [24] as follows:

$$dist_{v_i^t} = \left|\frac{f \times h_{v_i^t} \times z}{h'_{v_i^t} \times h_s}\right|, \tag{3}$$

where $h_{v_i^t}$ represents each vehicle's real height, f is camera focal length, z denotes the vertical dimensions of the captured frame, $h'_{v_i^t}$ is the height of the graphic image produced in pixels at time t and h_s is the height of camera's sensor. As our particular circumstances are based on the static camera's position, the angle is calculated by pixel position of vehicles' bounding box. To acquire this result, we assume the RSC orientation as the specified position of 0 degree in pixels. Based on theorem of Pythagorean and trigonometric function, we can calculate the angle of each vehicle towards RSC as follows:

$$angle_{v_i^t} = \left|arcsin\left(\frac{x_{v_i^t}}{y_{v_i^t}}\right) - arcsin\left(\frac{x_c}{y_c}\right)\right|, \tag{4}$$

where $x_{v_i^t}$ represents the length from outer corner of each vehicle's bounding box towards the vertical center of the specific image, x_c stands for proximity from x position of RSC's orientation in pixel towards the vertical center of the image, $y_{v_i^t}$ represents the width acquired from top position of each vehicle's bounding box position towards the bottom of the frame vertically, while y_c denotes the width produced from y position of RSC's orientation in pixel towards the bottom of frame vertically.

2) 3D Distance and Angle Calculator Module: From the RSC view side in Fig. 3, RSC location is defined as loc_c. MEC server will receive some messages $B^t = \{b_1^t, b_2^t, ..., b_o^t\}$ transmitted from each vehicle in which each $b_j^t, j \in \{1, 2, ..., o\}$ is defined as the location of the vehicle itself $loc_{b_j^t}$. Furthermore, the distance between RSC and b_j^t, along with the angle derived from RSC and b_j^t shall be derived correctly. To obtain the distance between two GPS locations, the haversine formula [25] can be applied as follows:

$$dist_{b_j^t} = \left|loc_c - loc_{b_j^t}\right| \tag{5}$$

In order to calculate the angle from the RSC towards vehicle, the bearing between the RSC and the vehicle can be obtained from the GPS receivers equipped on the RSC and the vehicle. Therefore, it can be calculated as follows:

$$\beta = atan2(A, B), \tag{6}$$

where A and B are two variables, which can be calculated as:

$$A = cos(Lat_{b_j^t}) \times sin(\Delta Long), \tag{7}$$

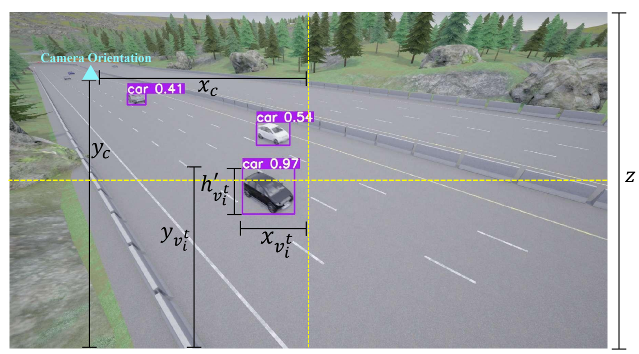
$$\begin{aligned} B = cos(Lat_c) \times sin(Lat_{b_j^t}) \\ -sin(Lat_c) \times cos(Lat_{b_j^t}) \times \Delta Long, \end{aligned} \tag{8}$$

Afterwards, it can calculate the angle from the RSC towards a certain vehicle by differentiating between the vehicle's bearing and the RSC orientation (obtained from the magnetometer equipped on the RSC) denoted as β and α respectively. In our experiment, the orientation is assumed as 0 when the magnetometer points towards the north.

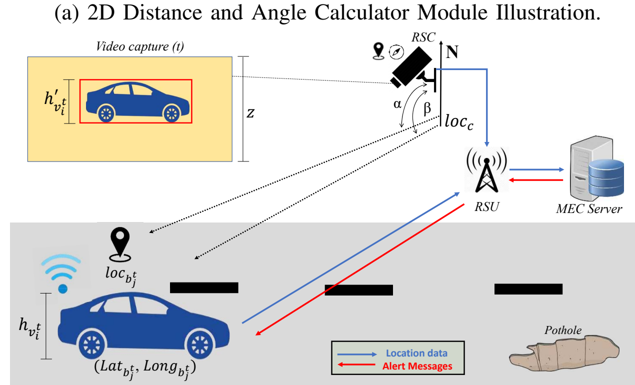
$$angle_{b_j^t} = |\beta - \alpha| \tag{9}$$

B. Information Classification

After performing the recognition and extracting the distance along with angle features, the next step is how to identify the vehicles and lane information. Subsequently, the necessary information shall be transmitted to the target vehicle. Since each lane may have various situations, the Information Classification block should be able to perform an accurate lane-level information transmission.



(a) 2D Distance and Angle Calculator Module Illustration.



(b) 3D Distance and Angle Calculator Module Illustration.

Fig. 3: Distance and angle calculation.

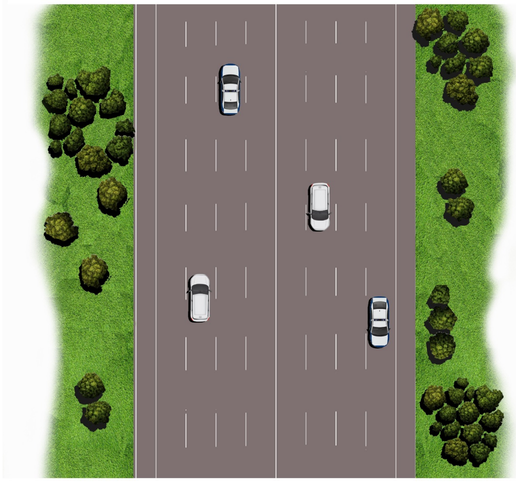


Fig. 4: The road map in our experiment.

1) Data Fusion Module: Since we already obtained the distance and angle values from 2D and 3D Distance and Angle Calculator module, we shall calculate the value of weight from each v_i^t in V^t and b_j^t in B^t to identify and locate the vehicle. From this calculation, a weight matrix shall be derived and defined as w_{ij}^t, $i = 1...n$, $j = 1...o$. Then the weight and confidence value shall be derived and given to each pair of (v_i^t, b_j^t). The distance and angle weight can be calculated with 2 steps as follows:

1) Distance weight: $max(\Delta dist)$ is the maximum distance difference between the results from 2D and 3D Distance Calculator modules.

$$dist_{w_{ij}^t} = \frac{max(\Delta dist) - min\left\{|dist_{v_i^t} - dist_{b_j^t}|\right\}}{max(\Delta dist)} \tag{10}$$

2) Angle weight: $max(\Delta angle)$ is the maximum angle difference between the result from 2D and 3D Angle Calculator module.

$$angle_{w_{ij}^t} = \frac{max(\Delta angle) - min\left\{|angle_{v_i^t} - angle_{b_j^t}|\right\}}{max(\Delta angle)} \tag{11}$$

Then, a total amount of weight is added to derive $w_{ij}(t)$.

$$w_{ij}^t = \left(dist_{w_{ij}^t} + angle_{w_{ij}^t}\right) \tag{12}$$

2) Vehicle Mapping Module: The weight matrix $\mathbf{W^t}$ is defined in Eq. (13) that has been derived from each b_j^t. In the previous data fusion module, the weight is used to score the position estimation of the vehicle. The most straightforward method is to select the highest score of the corresponding pair.

$$\mathbf{W^t} = \begin{bmatrix} w_{11}^t & w_{12}^t & ... & w_{1j}^t \\ w_{21}^t & w_{22}^t & ... & w_{2j}^t \\ ..... & & & \\ w_{i1}^t & w_{i2}^t & ... & w_{ij}^t \end{bmatrix} \tag{13}$$

TABLE I: Weight table for every transmission time t

weight	v_1^t	v_2^t	v_3^t
b_1^t	92	94	60
b_2^t	35	90	40

However, in Table I, we can see that although the highest score is v_2^t and b_1^t, the scores of v_1^t and b_1^t are both high. On the other hand, the score v_2^t and b_2^t is much higher than (v_1^t,b_2^t). Thus (v_1^t,b_1^t),(v_2^t,b_2^t) might be a better choice. To solve this situation, we define a confidence function $(C(w_{ij})^t)$ to choose w_{ij}^t:

$$C(s_{ij}^t) = \frac{max_{i=1}^n \ weight(w_{ij}^t, v_i^t)}{\sum_{i=1}^n \ weight(w_{ij}^t, v_i^t)}, \tag{14}$$

Intuitively, if s_{ij}^t of v_i^t and b_j^t is much higher than s_{ij}^t of others, $C(s_{ij})^t$ will be higher. Therefore, the Vehicle Mapping module shall be conducted by following steps:

Step 1: Filter the instance for those estimated vehicle positions which available on the image (threshold = 0.8).
Step 2: Calculate the weight for estimated positions of the filtering process and get the weight table.
Step 3: Calculate the confidence function for each estimated position in the table.
Step 4: Analyze the confidence score from the higher confidence to the highest weight which is not matched yet.
Step 5: Match the v_i^t and b_j^t respectively.

3) Lane Mapping Module: The RSC's location is static and the vehicles should be classified into different lanes based on its location. As explained in the previous step, the information of road lanes and vehicles are already acquired. The next step is to pair the lane region with the group of vehicles. Our goal is to classify the vehicles mapped in M^t on each lane. To deliver the information to the target vehicles, we classify the vehicles on each lane as follows:

$$V^l = \left\{v_i^t \mid lane(v_i^t) = l \ and \ l \in L\right\}, \tag{15}$$

In this case, l is the specific lane which target vehicles located. Every vehicle detected previously will be classified into the corresponding lane as long as it is located in the lane region. Then, through this formula, the transmission to the vehicles in the expected lane will be able to be conducted.

4) Precise Data Transmission Module: After going through Vehicle Mapping and Lane Mapping module, we are aware of lane-scale vehicle information. At this phase, the alert or traffic information can be precisely transmitted to the target vehicles at the specific lane. Therefore, as Table II shows, the format of the notification messages is {<condition><position>}. E.g. {1F} shows that the pothole will be in front of the vehicle. On the other hand, the caution message is used to alert other surrounding vehicles whether the vehicle might change lanes into their lane.

TABLE II: Alert messages

Type	Messages
1	Danger
2	Caution
F	Front
L	Left
R	Right

C. Delay Analysis

The total delay T is computed by the amount of the t^{comp} and t^{comm} where t^{comp} represents processing delay and t^{comm} represents transmission delay. These can be calculated by Eqs.(16) - (17):

$$T = t^{comp} + t^{comm}, \tag{16}$$

$$t^{comm} = \frac{m}{C}, \tag{17}$$

where m is the message size and C is the communication link capacity (bandwidth). Assuming that the bandwidth used in our experiment is the IEEE 802.11p standard [26].

IV. EXPERIMENTAL RESULTS

CARLA simulator [27] has been used to evaluate the vehicle identification and data transmission of the proposed method. In these experiments, RSC is deployed on the road to obtain graphic images to expand our surrounding awareness towards the road environment. Meanwhile, several vehicles are arranged on the road with different speeds and locations to assess these experiments. The simulated environment is a 500 meter long four-lane road. This road has two opposite lanes and also a contoured road condition as shown in Fig. 4. On the other hand, we record the location of the vehicle at a certain time. YOLO version 3 [18] is used to find the bounding boxes of the vehicle in Fig. 3(b) shown by the graphic image obtained from RSC.

We verify the proposed data fusion driven lane-level precision system model through three experiments. To evaluate our system model performance, the lane-level accuracy formula on Eq. (18) for total vehicles and Eq. (19) for vehicles on each lane are defined. $\hat{v}$ and N denote the identified vehicles and total number of the vehicles, respectively.

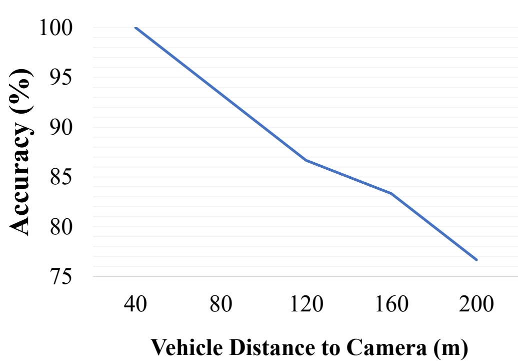


Fig. 5: Vehicle recognition distance (m).

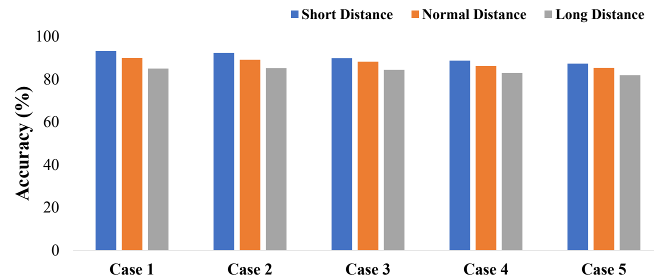


Fig. 6: Comparison of vehicles accuracy based on number and the distance of vehicles.

$$Acc = \frac{\sum_{t_0}^{t_n} N_{\hat{v}}^{t}}{\sum_{t_0}^{t_n} N_{v}^{t}}, \tag{18}$$

$$Acc^{l} = \frac{\sum_{t_0}^{t_n} N_{\hat{v}^{l}}^{t}}{\sum_{t_0}^{t_n} N_{v^{l}}^{t}}, \tag{19}$$

In the first experiment, we simulate the accuracy versus vehicle recognition distance for one vehicle in Fig. 5. We can observe that while the vehicle distance to RSC increases, the accuracy will be decreased. From 30 experiments, the results of the accuracies are 96.67% at 40 meters and 76.67% at 200 meters. In the second experiment, we consider five cases (case 1 to case 5) in Fig. 6, where case 1 has five vehicles and five more vehicles will be added for each of the next case respectively. In Fig. 6, each case considers short distance, normal distance, and long distance for the comparison of vehicles accuracy based on number and the distance of vehicles. The short distance, normal distance, and long distance are defined as 0-80 meters, 80-160 meters, and 160-200 meters, respectively. We observe that short distance in each case has the best accuracy and different number of

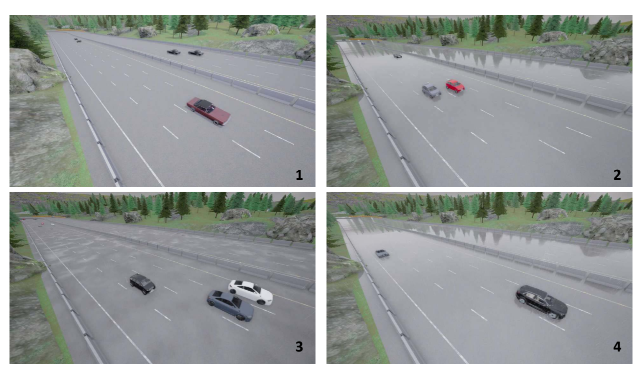


Fig. 7: Simulation experiment with different weather (1) clear, (2) soft rain, (3) mid rain, (4) heavy rain.

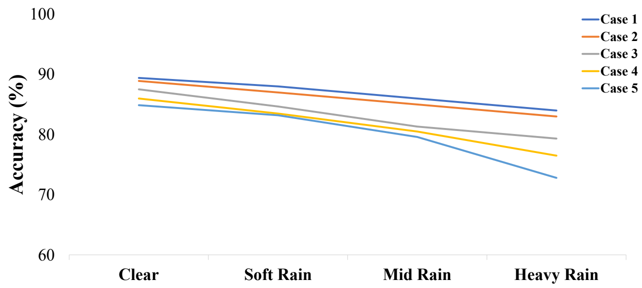


Fig. 8: Accuracy of the system under different environment.

vehicles affects the accuracy value. The average accuracies for three distances are 90.32%, 87.79%, 83.92%, respectively.

In the third experiment, we consider the effects under different environments in Fig. 7, including clear, soft rain, mid rain, and heavy rain. The average accuracy reduction in Fig. 8 is around 6% between clear weather and hard rain weather. From above three simulations and verification, even in 25 vehicles, the accuracy can be satisfied to enhance the driving experiments. Our experiment shows that delay transmission is less than 72 ms as shown in Fig. 9. Since our experiment is in line with the recommendations from ITU-T G-114 [28], our experiment is proved feasible to be applied. G-114 states that communication system should have a one-way delay of maximally 150 ms.

V. CONCLUSION AND FUTURE WORKS

In this work, in order to achieve better driving experience, the following designs are conducted. 1) Propose the data fusion driven lane-level precision system model by fusing vehicle data via OBU and video data via RSC. 2) Consider three type information including video, GPS and magnetometer. 3) Propose the vehicle mapping method to pair the vehicle and broadcast information. 4) Propose the lane mapping method to pair the vehicle and lane. From the experiments, we can observe that the accuracy can attain 87.34% on average with total delay less than 72 ms. Thus, we can precisely deliver the necessary information to the needed vehicles. Other vehicles will not receive the necessary information to avoid generating garbage messages. Ultimately, the drivers can enjoy their driving experience according to this useful information transmission via the proposed system model. In the near

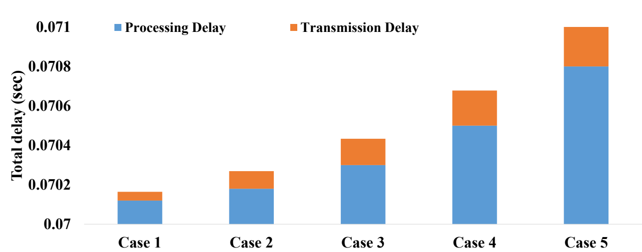


Fig. 9: Total delay of data fusion driven lane-level precision data transmission.

future, we can scale up the number of RSCs to explore the optimization of the proposed method.

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