Performance Evaluation of Object Detection Considering C-V2X Communication Errors

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***Abstract*—To cope with the issue of high computational loads in vehicles equipped with multiple sensors for safe autonomous driving, vehicular edge computing (VEC) has been proposed. When applying VEC, it is important to analyze the recognition performance considering communication errors because data quality can be degraded due to communication errors, which can result in decreased recognition or processing performance. Previous studies have mainly focused on aspects such as delay and cost. However, there is a need for analysis specifically addressing recognition performance in light of communication errors. This paper suggests the optimal sensor resolution to enhance object detection performance based on the signal-to-noise ratio (SNR). We analyze the performance of each resolution according to SNR. Based on these results, we anticipate that selecting the optimal resolution for object detection based on channel conditions during offloading can further improve driving safety.**

***Index Terms*—Vehicle-to-everything (V2X), vehicular edge computing (VEC), offloading, autonomous driving, object detection**

I. Introduction

Towards fully autonomous driving, accurately perceiving the surrounding environment is crucial. To achieve this, an increasing number of sensors, such as camera, radar, and lidar, are required for object detection, lane detection, cruise control, traffic sign recognition, and path planning. However, with increased variety and quantity of sensors in vehicles also result in higher computational loads. Vehicular edge computing (VEC) has emerged as a proposed solution to alleviate high computational loads. VEC combines vehicle-to-everything (V2X) communication and edge computing to reduce the computational burden on the vehicle [1]. By offloading computational tasks, the vehicle's computational load and data processing time can be reduced. Previous studies have focused on factors such as delay, cost, energy consumption, and resource management [2], [3]. These studies have conducted research under ideal conditions without considering communication errors. However, in realistic VEC environments, communication errors inevitably occur during the process of offloading vehicle sensor data to the edge server. In this case, the sensor data with errors consequently can result in the deteriorating performance of object detection. Therefore, we analyze the object detection performance of the camera sensor data which has communication errors.

This paper aims to enhance object detection performance by evaluating camera data of different resolutions based on the signal-to-noise ratio (SNR), ultimately providing optimal object detection results. Though most of the V2X channel has the line-of-sight (LOS) in most situations, hazardous scenarios with obstructed LOS, such as trucks and buildings, can have degraded channel quality and induce casualty and traffic accidents. Although non-line-of-sight (NLOS) situations are not as common as LOS scenarios, considering these issues is crucial for ensuring the seamless operation of vehicle applications even in challenging environments, which is of paramount importance in terms of safety for achieving fully autonomous driving. Hence, we conducted simulations to analyze the performance of different resolutions in the NLOS edge computing scenario. Through these simulations, we were able to determine the optimal resolution based on the SNR values.

II. Methodology

A. Scenario

To analyze the impact of the object detection performance of the offloaded camera sensor data with communication

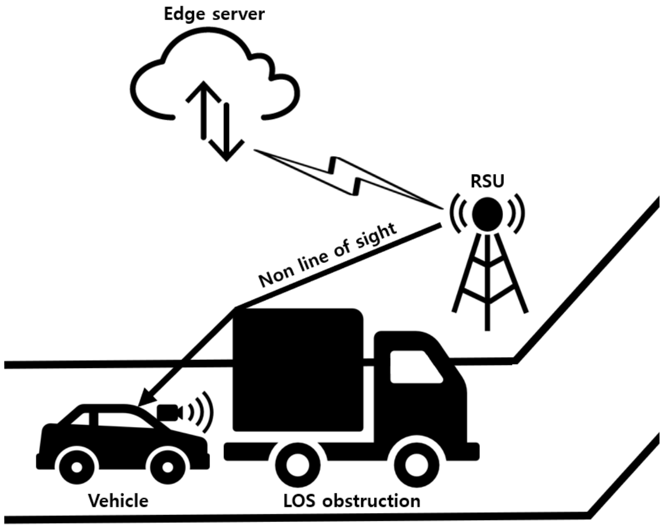

Fig. 1. V2X-enabled real-time sensor data offloading and processing in NLOS edge computing scenario

errors, as depicted in Fig.1, the vehicle transmits the real-time camera sensor data for object detection on the NLOS channel to the edge server using V2X. To simulate the NLOS environment, we configured a scenario where there is a LOS obstruction between the road side unit (RSU) and the vehicle. The RSU, which is located alongside the road, receives sensor data from the vehicles and the edge server near RSU processes the received sensor data from RSU. When it comes to communication, larger data sizes are more vulnerable to communication errors. It may not be practical to transmit a high-resolution image without considering the increased vulnerability to communication errors. Therefore, in the context of offloading, unconditionally sending a high-resolution image may not be a reasonable approach. To find the optimal sensor resolution according to the SNR, we conducted the simulation to evaluate the object detection accuracy of images at different resolutions based on the SNR.

B. Toolkits and Datasets

Berkley deep drive (BDD) 100K dataset: BDD100K dataset is suitable for training and evaluating object detection algorithms in the context of autonomous driving due to its coverage of various weather conditions, lighting conditions, and driving scenarios [4]. It includes a diverse range of objects encountered on the road, such as pedestrians, vehicles, bicycles, and traffic signs, providing a realistic representation of the objects that autonomous vehicles need to detect and respond to.

To simulate the transmission of camera data, we utilized the BDD100K dataset and resized the images to generate samples with different resolutions. By utilizing these images, we examined the impact of varying image resolutions on the performance of object detection algorithms, considering communication errors that occur with different resolutions.

You only look once (YOLO) v7 algorithm: YOLOv7 is the state-of-the-art object detection model that improves performance and accuracy in real-time scenarios [5]. It strikes a balance between accuracy and speed, making it suitable for real-time applications. In this paper, we train the BDD100K dataset using YOLOv7, focusing on six classes: car, traffic sign, traffic light, person, truck, and bus. Subsequently, we evaluated the mean average precision (mAP) of each resolution using the trained YOLOv7 model.

WiLabV2Xsim: To simulate cellular vehicle-to-everything (C-V2X) communication environment, we used WiLabV2Xsim, a system-level simulator based on MATLAB [6]. WiLabV2Xsim allows us to replicate and study the dynamics of C-V2X communication by adjusting various parameters related to the communication system. By leveraging WiLabV2Xsim, we can effectively evaluate the performance and reliability of the C-V2X communication environment.

C. Simulation Setup

Consequently, we utilize this simulator to simulate vehicles transmitting camera data with different resolutions to an edge server via C-V2X. We have employed the Winner+ B1 channel model, which encompasses the methodology outlined by 3GPP for calculating path loss in vehicular communications. This methodology takes into account an antenna height of 1.5m and computes correlated shadowing using a log-normal distribution with a 4 dB standard deviation in NLOS environment [6]. Furthermore, we modify the original simulator to generate packet loss patterns during the transmission of camera data. These obtained packet loss patterns are then applied to the original dataset, which comprises images of various resolutions, thereby simulating corrupted images caused by packet loss in the C-V2X communication environment. We perform object detection using YOLOv7 and analyze the resulting mAP to assess the accuracy of object detection under different resolutions and error patterns.

III. Results and performance analysis

The success or failure of message transmission relies on the signal-to-interference-plus-noise ratio (SINR). The equation for measuring SINR at the receiver vehicle is as follows.

$$SINR = \frac{P_{TX} \times pathloss}{\sum_{i=1}^{N} P_{TX,i} \times pathloss_i + Noise}, \quad (1)$$

where $P_{TX} \times pathloss$ is the received power from the transmitting vehicle, $\sum_{i=1}^{N} P_{TX,i} \times pathloss_i$ is the interference power caused by other vehicles, and $Noise$ is the noise term. Successful reception occurs when the SINR exceeds a certain threshold. The simulation process involves comparing the SINR of each transmission with the threshold. After the simulation concludes, the reception outcomes are compiled to compute the packet delivery ratio (PDR), which signifies the proportion of successfully received packets. Meanwhile, our dataset comprises images with varying resolutions. These images underwent evaluation utilizing the YOLOv7 algorithm, which incorporates an intersection over union (IoU) threshold of 0.5 to ensure accurate assessment.

Larger sensor data can be transmitted using a high modulation and coding scheme (MCS), but higher MCS order increases vulnerability to communication errors. On the other hand, using a low MCS provides relative resistance to errors, but reduces the amount of data that can be transmitted. Consequently, despite utilizing the same resource, each resolution utilizes a different MCS, leading to varying effects on communication errors. As a result, the quality of received data differs according to resolution, ultimately affecting the mAP results for object detection. Therefore, we recommend selecting an appropriate camera resolution based on the SNR, as determined by the mAP result.

We evaluated the PDR across different resolutions and SNR values using the WiLabV2Xsim MATLAB-based system-level simulator. At SNR levels above 53 dB, no errors occurred across all resolutions. However, as the channel condition has deteriorated, communication errors probability have increased. Under high SNR conditions, the error performance was similar regardless of resolution. In contrast, under low SNR conditions, higher resolutions were associated with increased communication errors.

Then we applied acquired PDR pattern to the images. By applying the packet loss pattern associated with each PDR result and considering both resolution and SNR, we evaluated the mAP. The findings revealed that the optimal resolution for achieving the highest mAP varies depending on the channel condition. Lower resolutions tended to yield lower mAP scores in terms of object detection. However, from a communication perspective, low-resolution images are more robust to the communication channel using a low MCS index. On the other hand, high-resolution images achieved superior mAP scores but were more susceptible to communication errors due to their reliance on a high MCS. Consequently, their mAP scores could significantly decrease. Therefore, the degradation in object detection accuracy varied depending on the chosen resolution, emphasizing the importance of selecting the appropriate resolution that maximizes object detection accuracy while considering the channel conditions.

IV. Conclusion

This paper investigates the influence of resolution on the accuracy of object detection for sensor data with errors. Our analysis focuses on the object detection accuracy at various resolutions, using the mAP metric, and its correlation with the SNR. Contrary to the conventional belief that higher resolutions always yield superior detection results, our findings demonstrate that the optimal resolution for object detection varies depending on the SNR. Our results can help develop optimized strategies that improve object detection performance.

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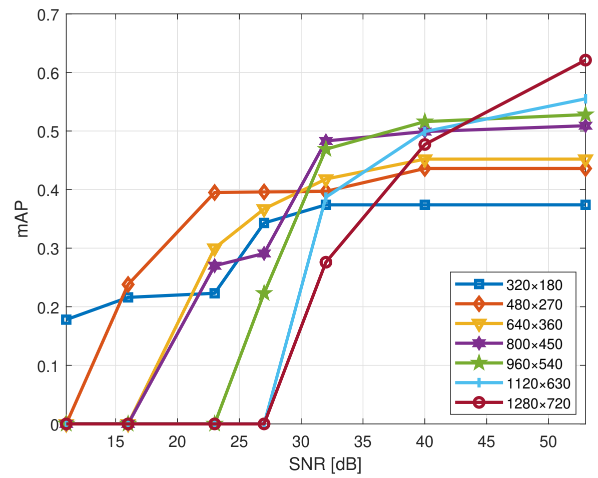

Fig. 2. mAP of each resolution with the communication error according to SNR in NLOS environment

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