Building a V2X Simulation Framework for Future Autonomous Driving

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***Abstract*—Collecting surrounding vehicles' motion information is one of the key issues for accident prevention and autonomous driving. Although multi-vehicle simulation frameworks are widely provided, We need a platform that enable inter-vehicle V2X communications. In this work, based on the open source simulation platform, CARLA, we extend and implement several modules to build a V2X simulation framework. In the proposed framework, vehicles are allowed to share their profiles and sensory data through V2X communications. With the motion information of other vehicles, a car can thus make more intelligent decisions. To validate the effectiveness of the framework, we run simulations in variose scenarios. Each time, a primary vehicle is selected and then both its sensory data and received surrounding vehicles' information are output and recorded in a simulated dataset. It is shown that with the dataset and our multi-vehicle data fusion algorithm, the primary vehicle can visually see the driving status of surrounding cars, which can greatly help a vehicle to choose a better driving strategy. This work not only proposes a V2X communication-enabled multi-vehicle simulation framework based on CARLA, but also provides a low cost way to generate simulated V2X datasets.**

Keywords: Autonomous Driving, Data Fusion, Sensing, V2X communication.

I. INTRODUCTION

Recent advances in sensing, wireless communications and mobile computing have enabled the development of driver assistance systems [1]. A lot of projects are aiming at SAE (Society of Automotive Engineers) level 4 or 5, i.e., full automation. Huge social and commercial values may be realized through collecting traffic and road information. Datasets such as KITTI [2] and Cityscapes [3] play a key role for the development of automatic driving algorithms. They contribute not only by allowing comparisons through benchmarking, but also by providing training before real test. Although rich types of data, such as video, LiDAR, and sensory data, are provided, V2X communications, which can help a vehicle to obtain its surrounding cars' information, are still missing.

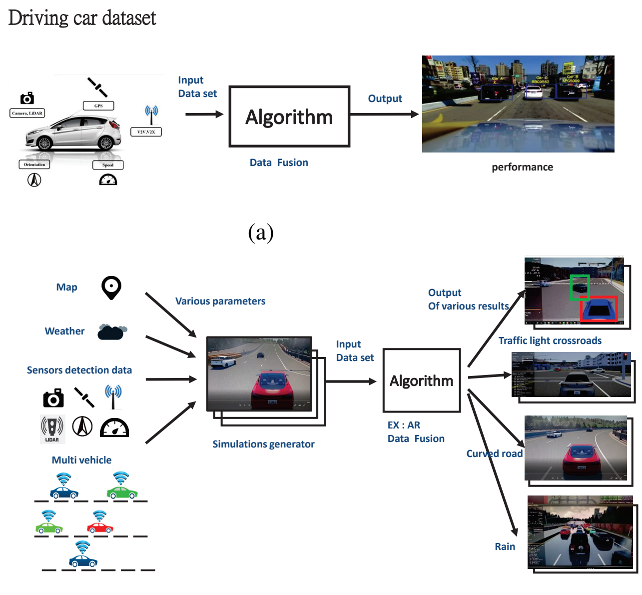
On the other hand, inter-vehicle communications have attracted a lot of interests in the communications society. Vehicular Ad Hoc Network (VANET) [4] [5] is an infrastructureless wireless network architecture providing local connectivity for V2V/V2I communications. However, having V2V/V2I communications does not imply that a vehicle would have full perception of its surroundings. The sensory data collected from vehicular communications needs to be well integrated before it is really meaningful. More specifically "to hear" (via communications) does not mean "to see" (via videos).

This paper intends to use a simulator to generate V2X dataset. The dataset includes raw images got from the cameras deployed on the primary vehicle, various sensory data(e.g., GPS, speed, and orientation), and even the profiles and sensory data of the neighbouring cars via V2X communication. Unlike traditional datasets, which provide road, weather, and traffic data as shown in Fig.1 (a), our multi-vehicle simulation framework allows us to simulate V2X communications and collect neighboring vehicles' information in addition to the aforementioned data. Fig. 1 (b) shows the variable, such as road map, weather condition, number of vehicles, time, and types of sensors, that can be simulated. In addition, surrounding vehicles' information can be collection through V2X communications. The goal of our platform is to generate such datasets for future autonomous driving design. We will show the features of our simulation framework, main components, and system architecture. At the end, an AR-driving assistive application is used as a use case to validate how to apply our framework to driver assistance applications. We shall show complete multi vehicle simulation framework use case, how to achieve this goal through data fusion techniques.

The rest of this paper is organized as follows. Section II reviews some related works. Section III formally defines our required features. Section IV proposes our system architecture. Section V shows our use case. Section VI concludes this paper.

II. RELATED WORK

Multi vehicle simulation frameworks have supported the development and validation of advanced driver assistance systems from the beginning. Some of the mostly commercial multi vehicle simulation frameworks are platforms such as $IPG\ CarMaker, TASS\ PreScan$ [6]. The recent open-source simulation platform $CARLA$ [7] presents the full complexity of urban road traffic, and many more, provides emulation of raw sensor data and simulates vehicle dynamics, all based on detailed physics models. These detailed environment models facilitate the test of the complete vehicle simulation framework. However, these frameworks all focus on simulating vehicle drivings in a near realistic way. Vehicle-to-everything (V2X) communications [8] are not included, which can help vehicles to get more information about surroundings. In addition, to the best of our knowledge, no one propose to generate vehicle road driving dataset via simulation framework so far.



(a)

(b)

Fig. 1: (a) Traditional simulation method. (b) Multi-vehicle simulation framework.

It is shown in [8] that localization errors may impact traffic flows and increase gas emission for automated vehicle control. Video-based location tracking is studied in [9]. It is more accurate but its coverage is usually limited. A 3D feature map is used in [10]. It requires a lot of pre-processing to build a digital map and it is not suitable for traffic jam areas. Back Lane Marking Registry (BLMR) is proposed in [11], which applies gyroscope, odometry and prior road information (a map) to estimate vehicle locations. It has been tested for autonomous driving in a rural road. Due to blocking of roof camera, BLMR can not provide lane level positioning. The survey vehicle proposed in [12] is equipped with Velodyne LiDAR (32E), IMU(KVH-1775), odometry, and high performance GPS (Applanix POS LV).

Data fusion techniques have been used for aggregating data from different sensors. The Kalman Filter (KF) and Particle Filter (PF) are often used for data fusion. The KF accomplishes this goal by linear projections, while the PF does so by a sequential Monte Carlo method. In a linear system with Gaussian noise, the KF is optimal. Since noise is nonlinear in outdoor environments, the PF may give better results. Federated Kalman Filter (FKF) with Grey Predictor (GP) is proposed for land vehicles in GPS-denied environments [13]. Data fusion techniques are applied to improve localization by combining several information sources [14]. In [16] to let a vehicle see its surrounding vehicles driving states, we propose a fusion algorithm to integrate several types of sensory inputs, such as V2V, GPS, camera, and inertial data. In this work, using the AR-driving assistance application as a use case, it is shown that the proposed simulation framework can help validate advanced driving assistance applications.

III. Required Features

Our goal is to build a V2X simulation framework and then use it to generate simulated datasets with a rich bound of scenarios. The output simulated dataset includes the image data of camera front view and back view of the primary car, the various sensing data of the primary car, and the sensing data, also the profiles of surrounding vehicles, through the V2X communications. Using these datasets as the input, advanced algorithms can be tested and check the performance.

The problem to be solved in this research is how to complete the V2X-enabled multi vehicle simulator which can generate immersive driving data sets. In the following, we describe the requirements (or features) of this simulator.

The required features can be decomposed of eight modules. They are a) Image Module, b) Sensor Module, c) Weather Module, d) V2X Communication Module, e) Geographic Information Module (Map Module). f) Vehicle Flow Module, g) Autonomous Driving Module, , and h) Dataset Generation Module. The required features of all six modules are described as follows.

A. Image Module

We consider to simulate a car which is equipped with a number of cameras for capturing 360-degree surrounding views of the car. For example, Fig. 2 (a) and Fig. 2 (b) are the camera front view and back view of the primary vehicle, respectively. With further calculation, these views can provide much information, such as surrounding vehicles' relative distances, orientation, for the advanced algorithms to be tested.

B. Sensor Module

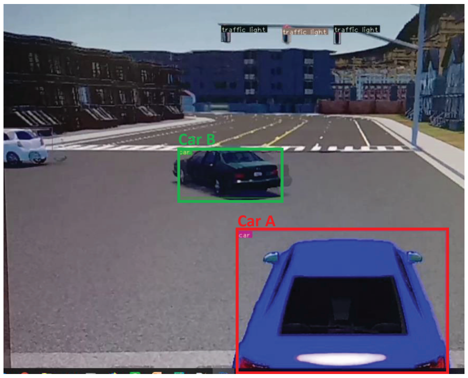
Each vehicle are equipped with a variety of sensors to provide its real-time status, such as GPS, speed, orientation, ..., etc. Via the V2X communication module, vehicles can exchange and share their sensor readings with surrounding cars, This can be used as a reference for advanced autonomous driving strategies. Currently, We suggest to at least support the sensors as follows:

- GPS sensor,
- Speed sensor, and
- Orientation sensor.

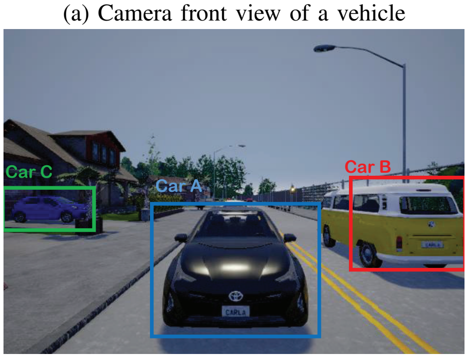
C. Weather Module

The module is to support to simulate a variety kinds of weather. For researchers, they can check whether the designed algorithm can work in all weather conditions. Moreover, the module has to provide different lighting conditions, such as day time, night time, driving to the sun, and back-lit. Currently, the following selections are allowed:

- Climate: sunny, rainy, or snowy day.
- Environmental lighting condition: day time, night time, to the sun, or back-lit.



(a) Camera front view of a vehicle



(b) Camera back view of a vehicle

Fig. 2: Camera view of a vehicle.

D. V2X Communication Module

V2X communications enable vehicles not only exchange information with other vehicles but share status with environments and other kinds of devices. This helps vehicles to understand more about road and vehicle/traffic conditions. Thus smarter driving strategies or reactions can be adopted [15]. Both IEEE and future 5G protocols support V2X communications. In the proposed V2X simulation framework, vehicles all at least support V2V communications. We model and simulate the vehicle-to-vehicle communications including the transmission delay and the packet dropping conditions.

E. Geographic Information Module (Map Module)

Users are allowed to choose different road maps to do their simulations. Several towns with different geographic information settings shall be provided in the simulation framework, thus researchers are able to test their proposed advanced algorithms in different cases.

F. Vehicle Flow Module

To test the performance of researchers' algorithms in different traffic conditions, the simulator has to support users to generate different degrees of vehicle flows in the simulation. The vehicle flow module is responsible to generate vehicle flows according to users' needs. Users' are allowed to set the start point, end point, and vehicle generating frequencies for a vehicle flow.

G. Automation driving Module

Researchers have to be able to develop and test their designed driving algorithms in the simulation framework. So the autonomous driving module is where researchers are allowed to add and implement their algorithms. If they need, parameters such as starting point, driving destination, and route path can be easily set through the module. Or they could implement the driving strategies by writing their codes.

H. Dataset Generation Module

When a simulation round is executed, the module is responsible for recording and logging the image and sensor readings of the primary vehicle from the image and sensor modules, respectively, and the profiles and sensory data of surrounding vehicles from the V2X communication module. Once the simulation round ended, all these data will be packaged and output as a dataset for further usage. With different settings for the simulators and several rounds of simulation executions, the dataset generation module can yield a quantity number of datasets for users to train and test their designed advanced driving assistance applications.

To satisfy and accomplish the above features, we develop the simulator based on the simulation platform, CARLA. CARLA is open source and has already provided several of the above modules (such as the weather, map, vehicle flow, and autonomous driving modules) or part of the functions (then only some extensions can help to complete our modules, such as the image and sensor modules). So two additional modules, the V2X communication module and the dataset generating module, have to be added and integrated into the platform to complete the proposed V2X simulation platform.

IV. SYSTEM ARCHITECTURE

Fig. 3 shows the configuration of a vehicle to vehicle communication platform. We assume that multi vehicle simulation framework has a V2X communication interface from ROS [15] as shown in Fig. 4, which is connected to a front/back camera, a LiDAR, a GPS receiver, and a magnetometer. The camera is to take surrounding videos for processing. The V2X interface periodically broadcasts the vehicle's profile and driving status and receives nearby vehicles' broadcasts. We propose a multi vehicle simulation framework for data fusion procedure in Fig. 2(b). Our system consists of three layer: a) Config Layer, b) Sensor Layer, c) Output Layer.

A. Config Layer

For each config layer, it is associated with the following information:

- The CARLA simulation tool provides basic climate setting features such as day, night, sunny, rainy days, and an array of geographic information to choose from.
- Use these modules and expand their functionality.
- In addition to the original scene, the weather module adds rain, and sets the light and backlight.

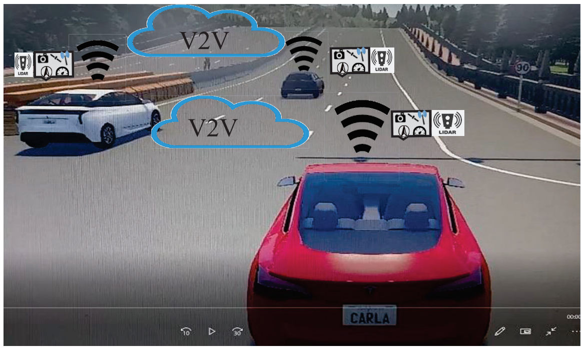


Fig. 3: Device configuration of a vehicle.

- Geographic information and building modules, add more maps, set the number of roads and maps.
- Self-driving modules that can be used with different vehicle shapes and colors.
- Spawn module, used to generate other vehicles in the environment, traffic settings and vehicle entry and exit point settings.
- Route senario module, which sets the route path of self-driving vehicles. These self-driving vehicles are also used to test the objects of self-driving algorithms or self-driving applications.

B. Sensor Layer

For each sensor layer, it is associated with the following information:

- Camera image module, using CARLA's own camera image modules, to obtain the target car front image.
- The LiDAR image module uses CARLA's camera image module to obtain images of all directions of the target self-driving car, combined with ROS and Rviz, to convert the 360-degree LiDAR image of the vehicle.
- Communication module, car and workshop exchange information and status of each vehicle, use Gamma distribution to simulate V2X communication loss rate and data transmit delay. (Gamma distribution [17] can approach a variety of different distributions, such as : $\alpha = \frac{E[t_d^2]}{V[t_d]}$, $\beta = \frac{\alpha}{E[t_d]}$).

$$f_G(t_d, \beta) = \frac{\beta^{\alpha} t_d^{\alpha-1} e^{-\beta t_d}}{\Gamma(\alpha)} \tag{1}$$

- Sensor module, currently implemented sensors, including camera, GPS, magnetometer, ..., etc., each vehicle can monitor the condition of the vehicle by means of sensors, and share the profile to the neighboring car through V2X communication. And to add the sensor's noise.
- We set up the ROS workspace behind the CARLA simulator, set up a Broadcast talk platform, use XML to write a broadcast platform, each car can broadcast its own information to other cars, and can also receive information about other cars.

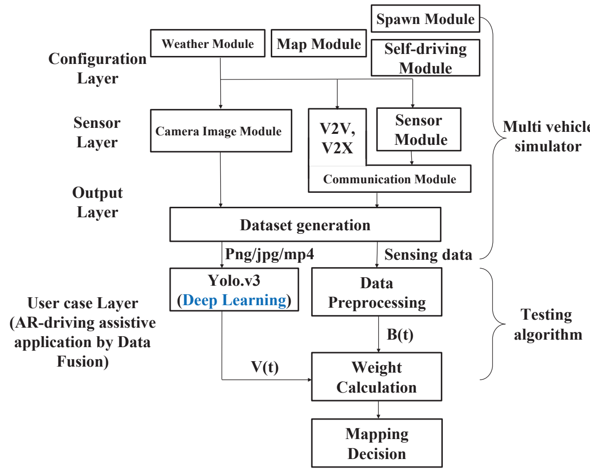


Fig. 4: Data fusion procedure.

C. Output Layer

This layer is responsible of each module output data. For each output layer, it is associated with the following information:

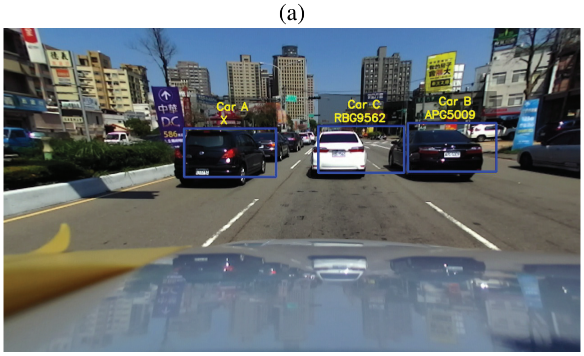
- DataSet generation, through the DataSet generation module output master vehicle image screen with their own and from the neighbor's profiles.

V. Use Case

In this section, we use a use case to validate the effectiveness of the simulate dataset generated by our V2X simulater, The use case is an AR-driving assistive application [16], in which the multi-sensory data from the primary car and received via V2X communications are integrated to help the car to understand its complex surroundings. As shown in Fig. 5, the driver can see the driving status and information of nearby vehicles via augmented reality (AR), which are achieved after identification, positioning and fusion. This helps the driver to drive safely. To provide a variety of scenes and more scalability for experiments and testing, we complete the simulator. In the following, we first show that datasets of many different scenarios can be generated. Then demonstrate the use case. Fig. 6 shows the simulated camera front view of a normal scene generated by the proposed simulator. We can see that Yolo can correctly identify the nearest two cars and give them ids. The farthest one is too far to be identified. Fig. 6 and 7 show the simulated camera view of the road congestion scene in sunny and rainy days, respective. In both cases, Yolo identification can work correctly.

In this part, we first briefly explain how the AR-driving assistive application work. Dataset generation module records and logs dataset from the V2X simulator. The image data can be a movie or a lot of pictures, such as png or jpg or mp4 file. Then, these picture are sent to Yolo deep learning to do identification, where identified vehicles will be bounded by bounding boxes and be labeling in $V(t) = \{v_1(t), v_2(t), ..., v_n(t)\}$. On the other hand, the recorded broadcast data, represented as $B(t) = \{b_1(t), b_2(t), ..., b_n(t)\}$, the information inside is like

(a)



(b)

Fig. 5: AR result of primary car.

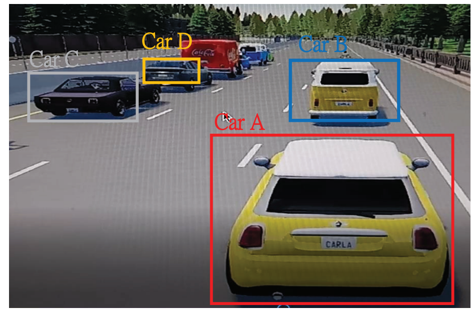


Fig. 6: Camera view and Yolo identification result of the road congestion scene.

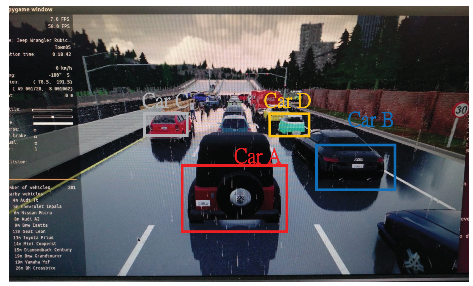


Fig. 7: Camera view and Yolo identification result of the road congestion plus rainy day scene.

the type of car, ID number, GPS positioning, head orientation, and speed, etc. These will be done the preprocessing first, mainly to calculate the distance and relative angle between them and the primary car. After identification and preprocessing, the processed data from these two sides are passed to the weight calculation, as show in Fig. 4. The weight $w_{ij}(t)$ is given to each pair $(b_i(t), v_j(t))$, which is a confidence value and $i = 1 \cdot \cdot M,\ j = 1 \cdot \cdot N$, When mapping, the highest confident weight will be selected from each $b_i(t)$ in $B(t)$ and $v_j(t)$ in $V(t)$ for pairing, thus a triplet $(b_i(t), v_j(t), w_{ij}(t))$ is formed and added to a list $SP(t)$. The next $b_{i+1}(t)$ will pick the highest confident match from the remaining weight, and so on. Finally the final mapping result is obtained Fig. 8 shows the pairing result by using the dataset generated by our V2X simulator. The result is similar with the real field trial as show in Fig. 5. Fig. 9 shows the weight variance of real field trial (Fig. 9(a)) and that of simulated dataset (Fig. 9(b)). The ranges of the two results are different because the scene in real field trial is more complex (more cars in Fig. 5 than in Fig. 8), so the confident weights in Fig. 8 are higher than that in Fig. 5.

VI. Conclusions

In this work, we propose and build a V2X simulation framework, in which vehicles are allowed to share their sensory data and profiles through V2X communications. With our simulator, users are able to test their V2X communication enabled intelligent autonomous driving algorithms. Moreover, the framework can help generating simulated dataset for various kinds of scenarios with low cost. We validate the effectiveness of simulated datasets generated by the simulator with an AR-driving assistive applications, which helps drivers' driving by augmenting car's identity and driving status on the real-time car video. The results show that assistive applications, which augmenting car's identity and driving status on the real-time car video. The results show that same augmenting outcome as real testing can be seen in the simulated car videos. So the simulation framework can help the development and validation of advanced driver assistive applications. In the future, we will further see whether more simulated datasets can improve the learning rate and prediction accuracy of algorithms.

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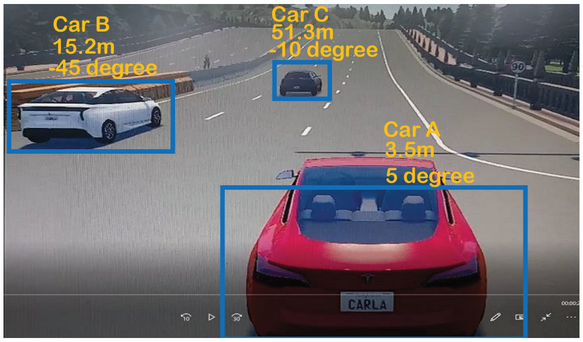
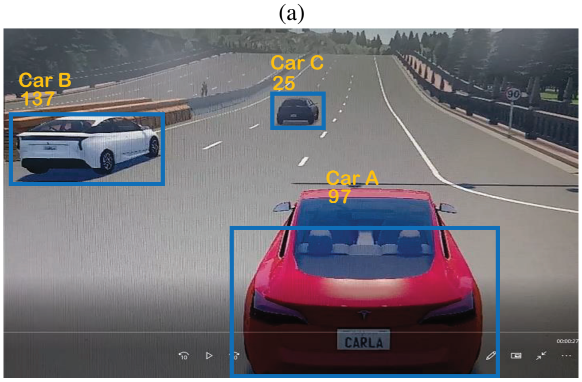
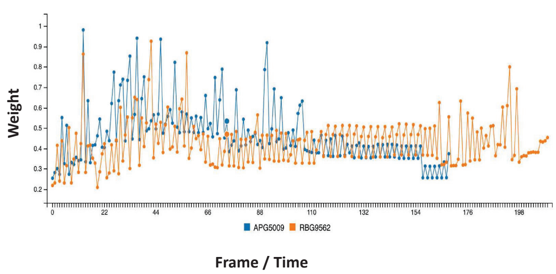


(a)

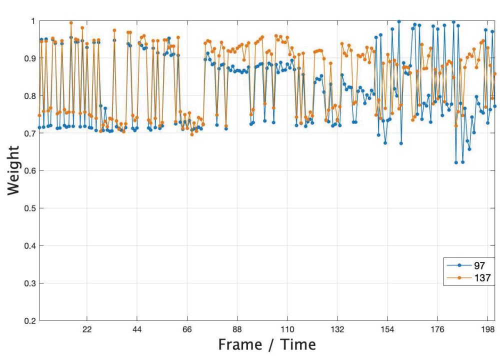


(b)

Fig. 8: An example of pairing result by using the dataset generated by the V2X simulator. (a) augmenting the driving status of cars and (b) augmenting the plate numbers of cars.



(a) Field Trials



(b) Simulated dataset

Fig. 9: Weight variances in field trials and simulated dataset.

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