V2X-Sim: A Virtual Collaborative Perception Dataset for Autonomous Driving

Yiming Li1, Ziyan An1, Zixun Wang1, Yiqi Zhong2, Siheng Chen3, Chen Feng1,∗
1New York University 2University of Southern California 3Shanghai Jiao Tong University
yimingli@nyu.edu, sihengc@sjtu.edu.cn, cfeng@nyu.edu
https://ai4ce.github.io/V2X-Sim/

Figure 1: (a) Intersection for vehicle-to-everything (V2X) communication. (b) RGB images from four vehicles passing through the same intersection. (c) Bird’s eye view (BEV) point cloud from vehicles and roadside infrastructure (each color represents an entity).

Abstract

Vehicle-to-everything (V2X), which denotes the collaboration between a vehicle and any entity in its surrounding, can fundamentally improve the perception in self-driving systems. As the individual perception rapidly advances, collaborative perception has made little progress due to the shortage of public V2X datasets. In this work, we present the V2X-Sim dataset, the first public large-scale collaborative perception dataset in autonomous driving. V2X-Sim provides: 1) well-synchronized recordings from roadside infrastructure and multiple vehicles at the intersection to enable collaborative perception, 2) multi-modality sensor streams to facilitate multi-modality perception, 3) diverse well-annotated ground truth to support various downstream tasks including detection, tracking, and segmentation. We seek to inspire research on multi-agent multi-modality multi-task perception, and our virtual dataset is promising to promote the development of collaborative perception before realistic datasets become widely available.

1. Introduction

The autonomous driving community has recently made great efforts in dataset construction to support research in this area, especially with perception and prediction [2–4, 11, 31, 38, 43]. Current efforts center around increasing the dataset scale [38], sensing modality [3], and downstream task diversity [2]. With the help of available datasets, researchers have proposed and validated novel methods to build more robust and efficient self-driving systems.

Notwithstanding the great progress in dataset construction, existing published datasets are all captured by single – rather than multiple – vehicles. This presents a gap in collaborative autonomous driving research. Vehicle-to-everything (V2X), which denotes the collaboration between a vehicle and other entities such as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I), seeks to help self-driving vehicles see further, better and even see through occlusion, thereby fundamentally improving safety. According to the estimation of U.S. NHTSA [1], there would be a minimum of 13% reduction in traffic accidents if a V2V system were implemented, which means 439,000 fewer crashes every year.

To fill in the gap in current research, it is an imperative to develop a well-established dataset for collaborative autonomous driving settings. Given that building such a dataset in the real world can be costly and laborious, we build a virtual dataset to advance collaborative perception...
research. Specifically, we employ SUMO [20], a micro-
traffic simulation, to produce numerically-realistic traffic
flow, and CARLA [8], a widely-used open-source simu-
lator for autonomous driving research, to retrieve the sen-
sor streams from multiple vehicles located at the same in-
tersection. Besides, we mount sensors on the traffic lights
to empower the roadside to perceive the environment, and
the sensor streams of both the vehicles and the roadside in-
frastructure are synchronized to ensure smooth collabora-
tion. In addition, multi-modality sensor streams of different
types are recorded to enable cross-modality perception.
Meanwhile, diverse annotations including bounding boxes,
vehicle trajectories, and pixel-wise as well as point-wise se-
mantics labels are provided to facilitate various downstream
tasks. Our dataset will be public and may inspire research in
multi-agent multi-modality multi-task perception before
realistic data becomes readily available to the community.

To summarize, contributions of this work are:

• We propose V2X-Sim, the first public collaborative
perception dataset in autonomous driving.

• We provide multi-modality data from multiple agents
to enable cross-modality perception.

• We provide diverse well-annotated ground truth to sup-
port various downstream tasks.

2. Related Work

Autonomous driving dataset. Since the pioneer dataset
KITTI [11] was released, the autonomous driving com-
unity has been trying to increase the dataset compre-
hesiveness in terms of driving scenarios, sensor modal-
ities, and data annotations. Regarding driving scenarios,
current datasets covered crowded urban scenes [31], ad-
verse weather conditions [33], night scenes [32], multiple
cities [3] to enrich the data distribution. As for sensor modal-
ities, nuScenes [3] collected data with Radar, RGB
camera, and LiDAR in a 360° viewpoint; WoodScape [43]
captured data with fisheye cameras; and A2D2 [12] pro-
vided extensive vehicle bus data including the steering
wheel angle, throttle, and braking. Regarding data annota-
tions, semantic labels in both images [7, 15, 30, 36] and
point cloud [2, 14] were provided to enable semantic seg-
mentation; 2D/3D box trajectories were offered [4, 9] to
facilitate tracking and prediction. In summary, existing
datasets generally emphasized the data comprehensiveness
in single-vehicle situations, but ignored the multi-vehicle
collaborative self-driving scenarios.

V2X system and dataset. By sharing information with
other vehicles or the roadside infrastructure, V2X mitigates
the shorting-comings of individual-vehicle perception and
planning such as the limited sensing range and frequent oc-
cclusion. Previous research [18] developed an enhanced co-
operative microscopic traffic model in V2X scenarios, and
investigated the effect of V2X in traffic disturbance scenar-
ios. [19] proposed a multi-modal cooperative perception
system that provides see-through, lifted-seat, satellite and
all-around views to drivers. More recently, [40] and [22]
included deep learning into the V2V system: multiple in-
elligent vehicles share the intermediate features output
by the neural network to promote the vehicle’s perception
capability. As for the dataset, [5, 24, 42] simulated the
V2V scenarios with different frames from KITTI [11]. Yet,
they were unrealistic for not capturing the measurements at
the same time. Some other works used a platoon strategy
for data capture [6, 34], but they were biased because the
observations were highly correlated with each other. [40]
proposed V2V-Sim based on a high-quality LiDAR simula-
tor [25]. Unfortunately, V2V-Sim does not include the V2I
scenario and is not publicly available.

Synthetic dataset. Simulation environments can help
generate large-scale datasets with well-annotated ground
truth. Current literature on computer vision has exploited
synthetic datasets in a wide array of tasks, e.g., visual track-
ing [10, 29], semantic segmentation [23, 35], flow estima-
tion [28], visual surveillance [39], visual odometry [35],
3D perception [41], multi-view stereo [21], and egocen-
tric localization [17]. Synthetic datasets not only enable
large-scale training through free and precise annotations,
but also support the cutting-edge research before realistic
data becomes readily available. An example of the latter
application is the long-range sensor in [41]. Multiple prior
works have proven that pre-training a model using syn-
thetic data can improve the model’s performance on the real
data [16, 27, 27, 37]. To further optimize such usage of syn-
thetic data, domain adaptation techniques [13, 26] are uti-
lized. In this work, we use a fully open-sourced autonomous
driving simulator, CARLA [8], to generate V2X-Sim.

| Sensor | Description |
|--------|-------------|
| V: 6 × RGB camera | Each vehicle is equipped with 6 cameras. Each camera has a FoV of 70°, except for the back camera that has a FoV of 110°. Each roadside has 4 cameras looking diagonally downward at 35° with a 70° FoV. The image size is 1600×900. |
| V: 6 × Depth camera | Each vehicle has 6 depth cameras with the same setting as RGB cameras. |
| V: 6 × Semantic camera | Each vehicle has 6 semantic segmentation cameras with the same setting as RGB cameras. |
| V&I: 1 × BEV semantic camera | Each vehicle and roadside has one BEV semantic camera at the top, looking downward. Both the raw images (semantic tags encoded in the red channel) and the converted colored images are provided. The image size is 900×900. |
| V&I: 1 × LiDAR and Semantic LiDAR | We attach one LiDAR and one semantic LiDAR on top of the ego vehicle and the intersection center. Specs: 32 channels, 70m max range, 250,000 points per second, 20 Hz rotation frequency. |

Table 1: Sensor specification of vehicle (V) and roadside infrastructure (I) in our V2X-Sim dataset. All the sensors are recorded at 5Hz.
Figure 2: Example of multi-agent multi-modality perception. From top to bottom: RGB image, depth, semantic segmentation, and BEV semantic segmentation. From left to right are respectively four vehicles’ recordings, except for the last row which appends an image of roadside in the last column.

Figure 3: Sensor layout and coordinate systems.

3. V2X-Sim Dataset

3.1. Sensor suite of vehicle and roadside

Multi-modality sensing data is essential for robust perception. To ensure the comprehensiveness of our dataset, we equip each vehicle with a sensor suite based on CARLA. It is composed of RGB cameras, depth cameras, semantic segmentation cameras, BEV semantic segmentation cameras, LiDAR, and semantic LiDAR. Meanwhile, the road infrastructure is equipped with RGB cameras, BEV semantic segmentation cameras, LiDAR, and semantic LiDAR.

Sensor configuration. On both ego vehicles and roadside infrastructure, the camera and LiDAR cover 360° horizontally to enable full-view perception. Specifically, each ego-vehicle carries six RGB cameras following nuScenes configuration [3]; the roadside infrastructure is equipped with four RGB cameras toward four directions at the crossroad. Note that the BEV semantic segmentation camera is based on orthogonal projection while the ego-vehicle semantic segmentation camera uses perspective projection. Table 1 summarizes the detailed sensor specification.

Sensor layout and coordinate system. The overall sensor layout and coordinate system is shown in Fig. 3, and one example of multi-agent multi-modality perception is shown in Fig. 2. On both ego-vehicle and roadside infrastructure, LiDAR and semantic LiDAR, RGB/depth/semantic cameras are placed at the same location to obtain depth/semantics ground truth. The BEV semantic segmentation camera shares the same x, y position with LiDAR yet is placed higher to ensure a certain size of field of view. As for the roadside infrastructure, sensors are placed at random heights within a realistic range to enhance
the diversity. Note that we invert the y-axis in CARLA and use right-hand coordinate system following nuScenes [3].

Diverse annotations. To assist downstream tasks including detection, tracking and semantic segmentation, we provide various annotations such as 3D bounding boxes, pixel-wise and point-wise semantic labels. Each box is defined by the location of its center in x, y, z coordinates, and its width, length, and height. Besides, there are totally twenty-three categories such as pedestrian, building, ground, etc. In addition, precise depth values are also provided for depth estimation.

3.2. CARLA-SUMO co-simulation

We consider it a realistic V2X scenario when multiple vehicles with their own routes are simultaneously located in the same geographical area, i.e., an intersection. The roadside infrastructures are also empowered by sensing capability. We use CARLA-SUMO co-simulation for traffic flow simulation and data recording. Vehicles are spawned in CARLA via SUMO, and managed by the Traffic Manager. The script `spawn_npc_sumo.py` provided by CARLA automatically generates a SUMO network in a certain town, and produces random routes to make vehicles roam around. Hundreds of vehicles are spawned in different towns (Town03, Town03 and Town05 that have cross junctions and multiple lanes per direction), and we record several log files, each with a length of five minutes. Then we read out 100 scenes from the log files at different intersections. Each scene includes a duration of 20 seconds, and we select $M (M = 2, 3, 4, 5)$ vehicles in a scene as the intelligent agents to share information with each other. See Fig. 4 for several example scenes.

3.3. Downstream tasks

Our dataset can not only support individual perception tasks such as 3D object detection, tracking, image-/point cloud-based semantic segmentation, depth estimation, but also enable collaborative perception like collaborative 3D object detection, tracking, and collaborative BEV semantic segmentation in urban driving scenes. We will provide a benchmark for the collaborative perception algorithms.

4. Conclusion

We propose V2X-Sim, the first virtual collaborative perception dataset in autonomous driving scenes based on CARLA simulator. By providing both multi-agent multi-modality sensor streams in realistic traffic flows and rich annotations, V2X-Sim can facilitate various perception tasks especially collaborative perception before realistic datasets become widely available. Our work seeks to inspire a variety of relevant research areas including but not limited to computer vision, multi-robot system, and deep learning.
Jakob Geyer, Y. Kassahun, M. Mahmudi, Xavier Ricou, Andreas Geiger, Philip Lenz, and R. Urtasun. Are we ready

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