



V2X-Real: A Large-Scale Dataset for Vehicle-to-Everything Cooperative Perception

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Abstract. Recent advancements in Vehicle-to-Everything (V2X) technologies have enabled autonomous vehicles to share sensing information to see through occlusions, greatly boosting the perception capability. However, there are no real-world datasets to facilitate the real V2X cooperative perception research – existing datasets either only support Vehicle-to-Infrastructure cooperation or Vehicle-to-Vehicle cooperation. In this paper, we present V2X-Real, a large-scale dataset that includes a mixture of multiple vehicles and smart infrastructure to facilitate the V2X cooperative perception development with multi-modality sensing data. Our V2X-Real is collected using two connected automated vehicles and two smart infrastructure, which are all equipped with multi-modal sensors including LiDAR sensors and multi-view cameras. The whole dataset contains 33K LiDAR frames and 171K camera data with over 1.2 M annotated bounding boxes of 10 categories in very challenging urban scenarios. According to the collaboration mode and ego perspective, we derive four types of datasets for Vehicle-Centric, Infrastructure-Centric, Vehicle-to-Vehicle, and Infrastructure-to-Infrastructure cooperative perception. Comprehensive multi-class multi-agent benchmarks of SOTA cooperative perception methods are provided. The V2X-Real dataset and codebase are available at <https://mobility-lab.seas.ucla.edu/v2x-real>.

Keywords: V2X Dataset · Cooperative Perception · Autonomous Driving

1 Introduction

The evolution of autonomous driving technology has been significantly accelerated by advancements in deep learning, particularly in perception tasks

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[9, 16, 22, 26, 37] crucial for safe navigation [8, 11, 27, 38] and decision-making [23]. While progress in various perception tasks has been notable, the single-vehicle vision systems still suffer from occlusions and limited perception range. The bottlenecks mainly stem from the fact that each vehicle can only assess its surroundings from a single view point, leading to a partial understanding of the environment. To address these issues, recent works [12, 15, 21, 25, 34, 35] have investigated Vehicle-to-Everything (V2X) Cooperative Perception, where each connected agent within the communication range can share the sensing information (*e.g.*, raw point clouds, detection results and intermediate neural features) with each other and leverage neighboring agent’s sensing information for visual reasoning to enlarge the perception range and see through occlusions.

Despite the great potential, there is no open V2X dataset from real-world scenarios for researchers to work with. The majority of available V2X datasets such as OPV2V [34], V2X-Sim [12] and V2X-Set [33] are generated through simulators [3] with simulated traffic dynamics and sensor renderings. This approach introduces a significant simulation-to-reality gap, thereby impeding the effective evaluation and deployment of V2X algorithms in the real world [31]. Recently, DAIR-V2X [35] and V2V4Real [31] present the pioneering real-world datasets for Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) collaborations. However, these datasets are limited by a single collaboration mode (*i.e.* either V2V or V2I), involving at most two agents within the same spatial vicinity. Nevertheless, in real world, V2X collaborations can dynamically adapt to multifaceted interactions inherent in real-world traffic scenarios, including V2V, V2I, I2I and thus truly V2X. Developing algorithms based on single collaboration mode will greatly constrain the scope of V2X collaborations and hinder deploying the algorithms in complex V2X scenarios. In addition, existing datasets are vehicle-centric by assuming the vehicle as the ego agent, ignoring the pivotal role of infrastructure; however, the infrastructure perception is vital for both autonomous driving and intelligent transportation systems. On the one hand, it can augment the perception systems of self-driving cars by sharing sensing information with nearby agents. On the other hand, infrastructure perception can provide a reliable basis for various intelligent transportation tasks such as traffic management, traffic monitoring and signal control, which will greatly benefit from the V2I and I2I collaborations. Moreover, DAIR-V2X [35] and V2V4Real [31] are mostly collected in suburban and rural areas with an average of 11–12 objects per scene. This relatively low traffic density limits their effectiveness in testing V2X cooperative perception in more challenging scenarios and restricts the scalability of V2X collaborations.

To this end, we introduce the V2X-Real, a large-scale multi-modal multi-view dataset tailored for V2X research, including 33K LiDAR frames, 171K camera images and over 1.2M 3D bounding box annotations. The proposed dataset is collected via two smart infrastructure and two autonomous vehicles equipped with full sensor suits (Fig. 1). To ensure the data diversity, we gather the data in two types of scenarios *i.e.*, V2X smart intersection and V2V corridors. With over 75 h of collected driving logs, we carefully curate and select 68 representative scenarios

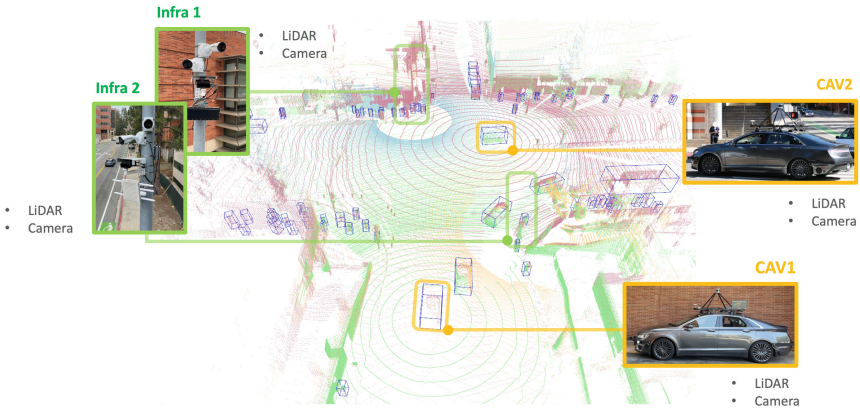


Fig. 1. Demonstration of smart intersection and overall data acquisition systems. Smart infrastructure (Infra) units and connected and automated vehicles (CAVs) are depicted in their combined LiDAR point clouds.

to form the final dataset. Unlike previous datasets, V2X-Real is primarily collected in urban environments, featuring an average of 36 objects per scene. Such environments offer a high density of traffic and a significant presence of vulnerable road users, providing rich challenging scenarios for V2X cooperative perception research. To innovate and support a wide range of research interests in V2X cooperative perception, the dataset is divided into four specialized sub-datasets based on the type of ego agent and their collaboration modes: V2X-Real-VC for Vehicle-Centric, V2X-Real-IC for Infrastructure-Centric, V2X-Real-V2V for Vehicle-to-Vehicle, and V2X-Real-I2I for Infrastructure-to-Infrastructure cooperative perception.

The key contributions can be summarized as follows:

- We build V2X-Real, the first open large-scale real-world dataset designed for V2X cooperative perception. According to ego agent’s type and its collaboration mode, we derive 4 sub-datasets tailored for vehicle-centric, infrastructure-centric, V2V and I2I cooperative perception.
- We provide over 1.2M annotated bounding boxes of 10 object categories with 33K LiDAR frames and 171K multi-view camera data.
- We conduct comprehensive benchmarks for multi-class multi-agent V2X cooperative perception for V2X-Real-VC, V2X-Real-IC, V2X-Real-V2V, and V2X-Real-I2I.

2 Related Work

2.1 Self-driving Datasets

Over the past few decades, a number of autonomous driving datasets have been released, greatly promoting the research and development of self-driving

Table 1. Comparisons of our dataset and existing autonomous driving and V2X dataset. V2V: Vehicle-to-Vehicle. V2I: Vehicle-to-Infrastructure. I2I: Infrastructure-to-Infrastructure. VC: Vehicle-Centric. IC: Infrastructure-Centric.

Dataset	Year	Type	V2V	V2I	I2I	Image (360°)	Agent Number	RGB images	LiDAR frames	3D boxes	Types
KITTI [5]	2012	Real					1	15k	15k	200k	8
nuScenes [1]	2019	Real				✓	1	1.4M	400k	1.4M	23
Waymo Open [19]	2019	Real				✓	1	1M	200k	12M	4
OPV2V [34]	2022	Sim	✓			✓	2.89	44k	11k	230k	1
V2X-Sim [12]	2022	Sim	✓	✓		✓	10	0	10k	26.6k	1
V2XSet [33]	2022	Sim	✓	✓		✓	2-7	44k	11k	230k	1
DAIR-V2X [35]	2022	Real		✓			2	39K	39K	464K	10
V2V4Real [31]	2023	Real	✓				2	40K	20K	240K	5
V2X-Real (ours)	2024	Real	✓	✓	✓	✓	4	171K	33K	1.2M	10
- V2X-Real-VC	2024	Real	✓	✓	✓	✓	4	145K	30K	1.1M	10
- V2X-Real-IC	2024	Real		✓	✓	✓	4	145K	30K	1.1M	10
- V2X-Real-V2V	2024	Real	✓			✓	2	140K	17K	719K	10
- V2X-Real-I2I	2024	Real			✓		2	31K	15K	470K	10

technologies. Among these datasets, KITTI is a pioneering autonomous driving dataset featured with full sensor suits [5]. Following KITTI, the NuScenes [1] and Waymo Open datasets [19] have expanded the scale of data significantly, offering both LiDAR point clouds and multi-view cameras that cover a 360-degree field of view, thereby enhancing the depth and breadth of research possibilities in the field. However, these datasets are all collected by a single vehicle. OPV2V introduces the first V2V cooperative perception dataset, created using CARLA simulator [3] and OpenCDA [29, 32, 36]. V2XSet and V2X-Sim [12] further extended to V2X scenarios in the CARLA simulator. In contrast to these simulated datasets, DAIR-V2X [35] is the first real-world dataset for V2I cooperative perception while V2V4Real [31] presents the first real-world V2V dataset collected by two connected vehicles.

Nevertheless, existing V2X datasets all focus on a single collaboration mode. Furthermore, the benchmarks and evaluations within these datasets are vehicle-centric, treating infrastructure merely as an auxiliary collaborator. Infrastructure-centric collaborations such as V2I and I2I are rarely discussed, highlighting a gap in the comprehensive evaluation of V2X interactions. A concurrent work, RCooper [6], introduces an I2I dataset for roadside cooperative perception. Compared with these datasets, our dataset features with all three V2X collaboration modes *i.e.* V2V, V2I, and I2I, and investigates and benchmarks both Vehicle-Centric and Infrastructure Centric V2X cooperative perception. Moreover, it is uniquely collected in congested urban environments with dense traffic and pedestrian flow, resulting in a record number of annotated 3D boxes compared to existing datasets. Furthermore, to facilitate multi-view camera-based perception, we will also provide multi-view stereo cameras covering 360 field-of-view for the vehicle agent and high-resolution network camera data for the infrastructure. Additionally, existing V2X datasets only benchmark the detection performance based on a single vehicle category, ignoring the perception performance for vulnerable road users. In contrast, we provide benchmarks for all the annotation types and will release our codebase for multi-class coop-

erative perception to facilitate V2X research on vulnerable road users, which is an important yet under-explored research area.

Table 2. Key Sensor Specifications in V2X-Real Dataset. Infra means infrastructure.

Agent	Sensor	Sensor Model	Details
Infra	LiDAR	Ouster OS1-128/64 ($\times 1$)	128/64 beams, 10 Hz capture frequency, 360° horizontal FOV, -16.6° to $+16.6^\circ$ (64), -22.5° to $+22.5^\circ$ (128) vertical FOV, ≤ 40 m range
	Camera	Axis-P14555 ($\times 2$)	RGB, 30 Hz capture frequency, 1920×1080 resolution, 76° horizontal FOV, 48° vertical FOV, JPEG compressed
	GPS	Garmin 18x LVC GPS ($\times 1$)	5 Hz update rate
Vehicle	LiDAR	RoboSense Ruby Plus ($\times 1$)	128 beams, 10 Hz capture frequency, 360° horizontal FOV, -25° to $+15^\circ$ vertical FOV, ≤ 200 m range
	Camera	ZED 2i ($\times 4$)	Stereo RGBD, 10 Hz capture frequency, 1920×1080 resolution, 120° horizontal FOV, JPEG compressed
	GPS/IMU	Gongji GPS System ($\times 1$)	1000 Hz update rate, Double Precision

2.2 V2X Cooperative Perception

Cooperative perception aims to enhance the perception capability of the V2X system by leveraging the shared information among connected agents. According to its fusion strategies, it can be broadly classified into three categories: 1) Early Fusion where the raw LiDAR point clouds are transmitted and the ego agent will aggregate the raw data to predict objects, 2) Late Fusion [17] where the detection outputs are circulated and then fused into a consistent prediction, 3) Intermediate Fusion [7, 13, 18, 21, 28, 33, 34] where the intermediate neural features are shared and fused. Though early Fusion preserves the raw information and thus can potentially reach higher accuracy, the high bandwidth requirement of transmitting raw data makes it infeasible in real-world scenarios. On the other hand, Late Fusion requires minimal bandwidth but loses the context information during transmission, resulting in inferior performance with compound errors. To strike a good balance between bandwidth requirements and accuracy, Intermediate Fusion has been gaining increasing attention. Att-Fuse [34] presents an attention-based fusion strategy to refine multi-agent’s BEV

features. V2VNet [21] employs a graph neural network architecture for joint perception and prediction. F-Cooper [2] presents a pooling mechanism to identify salient features. V2X-ViT [33] and CoBEVT [30] employ a sparse vision transformer for V2X collaborations. HM-ViT [25] presents a 3D heterogeneous graph transformer for camera and LiDAR fusion.

3 V2X-Real Datasets

To facilitate the V2X research, we present V2X-Real, the first large-scale real-world V2X dataset for cooperative perception. In this section, we first detail the data acquisition in Sect. 3.1, then present the data annotation and processing pipeline in Sect. 3.2, and finally discuss the diverse data distribution and dataset statistics in Sect. 3.3.

3.1 Data Acquisition

Sensor Specifications: The dataset was gathered using two connected and automated vehicles and two smart infrastructure. Each of the vehicles is outfitted with a 128-beam LiDAR, four ZED 2i Stereo Cameras, and a GPS/IMU integration system. The four cameras are strategically positioned on the front, rear, left and right sides of the vehicle to achieve a full 360-degree field-of-view (FoV). Similarly, each infrastructure unit is equipped with a 128(64)-beam LiDAR, two Axis high-resolution network cameras and a GPS to ensure precise time synchronization among the distributed devices. Detailed specifications of these sensors are provided in Table 2.

Data Collection: To ensure the diversity of our V2X data, We collected our data in two types of scenarios – V2X intersection and V2V corridor. In the intersection scenarios, two smart infrastructure units and two autonomous vehicles are operated simultaneously. Our autonomous vehicles will follow pre-defined routes, covering different V2X interactions. Through a combination of basic maneuvers of each autonomous vehicle at the intersection – such as left turn, right turn, waiting for a traffic signal, and going straight – we designed a total of 50 distinct V2X interactions in our dataset including car following, two cars driving towards each other, two cars making left (right) turn together *et al.* As the V2X data is primarily collected in a single smart intersection and its surrounding streets for diverse V2X interactions, to enlarge the diversity of our dataset, we further collected separate V2V scenarios in urban corridor. In these V2V data, we designed 10 types of V2V interactions, including car following, lane change, and overtaking between two autonomous vehicles *et al.*

Our data collection efforts span 3 months in diverse illumination conditions, with a total of over 75 h of collected driving logs. We carefully curate the data and select 68 representative scenarios for annotation with a total of 33K LiDAR frames and 171K Camera images, providing a rich resource for V2X research.

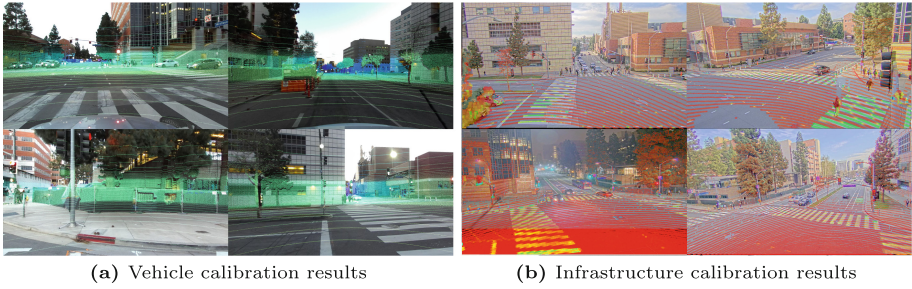


Fig. 2. Visualization of calibration results for (a) vehicle and (b) infrastructure (better viewed in color and zoomed in). The LiDAR points are projected onto the camera plane using the camera intrinsics and camera-LiDAR extrinsics.

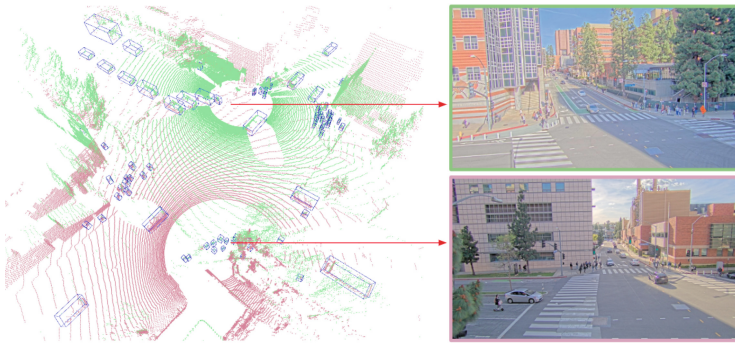


Fig. 3. Demonstration of combined LiDAR annotations for infrastructure. LiDAR points from different agents (green and pink) are aggregated for the same object, reducing half of the infrastructure annotation workload and enhancing annotators' ability to identify objects accurately and efficiently. (Color figure online)

Coordinate System: There are three types of coordinate systems in our dataset, namely the LiDAR coordinate, the camera coordinate, and the map coordinate. Each agent maintains a separate LiDAR and camera coordinate frame. We built a dense LiDAR point cloud map [24] covering all the driving routes and leverage map matching combined with GPS/IMU positional inputs [4] to identify the transformation between each agent's LiDAR coordinate frame and map coordinate. For 3D-2D associations, intrinsic and extrinsic calibrations between the camera and LiDAR are conducted. The visualization of the calibration result is shown in Fig. 2.

Synchronization: For the multi-agent datasets, it is crucial to synchronize the time clock of all agents. We synchronize all the computer's time clock with GPS time to ensure consistent timestamp across sensing messages and further lock the LiDAR phase with GPS signals to ensure the temporal synchrony of multi-agent sensing observation. As the ZED2i stereo camera and Axis network

camera cannot be hardware-triggered with GPS signals for synchronization, we post-process the collected data to identify the closest camera message as per LiDAR frame to reach minimal time difference. Messages with a large time gap are filtered to ensure suitable synchronization between multi-agent multi-modal data.

3.2 Data Annotation and Processing

We leverage the open-sourced labeling tool called SUSTechPOINTS [10] to annotate 3D bounding boxes. Expert annotators are employed to make high-quality annotations with a stringent review and revision process in place. On average, each scenario goes through 5–6 rounds of review and revision to guarantee accuracy and quality. In our dataset, there are in total 10 categories of annotated objects including pedestrian, scooter, motorcycle, bicycle, car, truck, van, box truck, bus and barrier on the road. For each object, we annotate its 9-dimensional cuboid containing x , y , z for the cuboid center, width, length, height for the cuboid extent dimension, and roll, yaw, pitch for the cuboid orientation.

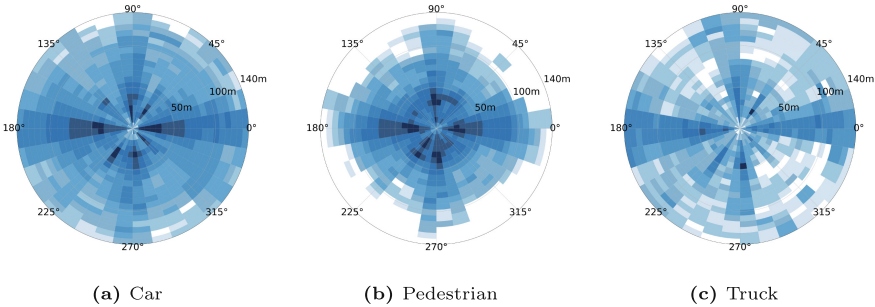


Fig. 4. Polar density map of annotated bounding boxes for (a) Car, (b) Pedestrian, and (c) Truck. The polar and radial axes represent the distance and angle of the bounding boxes respectively in the ego coordinate frame. The color indicates the number of boxes in the bin and the darker color corresponds to a larger density. (Color figure online)

Additionally, we have implemented several strategies to enhance the efficiency and accuracy of the annotation process. We combine two infrastructure’s LiDAR point clouds to form a holistic view for annotation (Fig. 3). The combined LiDAR point clouds can efficiently reduce the annotation workload and provide dense sensing measurements for objects of interest, greatly increasing the annotation efficiency and accuracy. After annotating the 3D boxes in combined LiDAR point clouds, we will project the boxes into each infrastructure’s coordinate frame and for each box, we will count the number of LiDAR points within the box. If the number is greater than a threshold (*i.e.*, 5 in our dataset), we will add the box to this infrastructure’s annotation result, otherwise, the box is ignored for this

agent due to its sparse sensing measurements. Afterwards, we manually check the result and refine the annotations for each of the agents. For vehicles, their poses vary from scene to scene with different levels of localization error, thus separate annotations for each of the vehicles are conducted to ensure accurate annotations. Additionally, for the static objects (*e.g.*, vehicles that are parked and those awaiting the change of a traffic signal), we provide annotators with a script to automatically interpolate their poses in one frame to a sequence of frames. This greatly increased the annotation accuracy and efficiency for static objects.

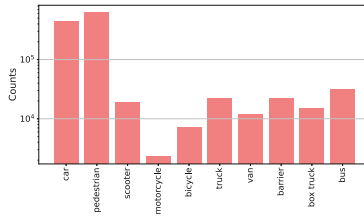


Fig. 5. Number of annotations per category in log scale.

As the objects are annotated separately in different agents’ coordinate frames, identical objects may be assigned with different IDs. To ensure consistent object ID, we project all the annotated boxes from different agents to the same map coordinate and calculate their IoU overlap. If their overlap is greater than a certain threshold, they are considered the same object and thus a unique ID is assigned.

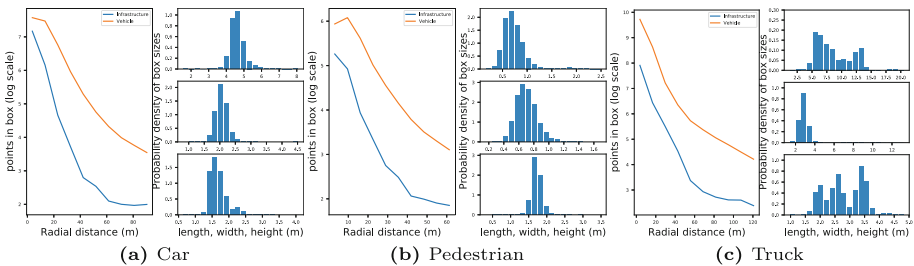


Fig. 6. Bounding box LiDAR point density distribution and box size distribution for (a) Car, (b) Pedestrian, and (c) Truck. In each category’s figure, the left figure depicts the number of lidar points within bounding boxes as per the radial distance from the data collection vehicle while the right figure demonstrates the bounding box size distribution.

3.3 Dataset Analysis

Our dataset has an average of 36 objects per scene with a maximum of 115 and a minimum of 9 objects, ensuring a high density of traffic in challenging urban scenarios. The number of annotations for each of the 10 categories is shown in Fig. 5. The dominant objects in the dataset are pedestrians and cars. Compared with the existing V2X dataset (Table 1), V2X-Real is featured with a wide variety and quantity of vulnerable road users including pedestrian, scooter, motorcycle, and bicycle. In our benchmarks, we group the 10 categories, based on their box sizes, into three super-classes *i.e.* pedestrian, car, and truck. In Fig. 4, we reveal the polar density map of annotated bounding boxes for these three classes, where each bin in the polar map represents a spatial area with a certain distance and angle range in the ego agent’s coordinate frame. From the figure, we can observe a diverse distribution of annotations and each category is denser in the front, left, right, and rare sides of the ego vehicle. We argue this is due to the fact that most of our data is collected adjacent to the intersection and the surrounding vehicles tend to have these four relative poses with respect to the data collection vehicle. Compared with car and truck categories, pedestrians have fewer annotations above 100m due to the sparse LiDAR measurements of the small objects in distant areas. Figure 6 depicts the point clouds density distribution within bounding boxes and the bounding box size distribution. From the figure, we can see the diverse bounding box size distribution and each category will have a size distribution and could serve as a prior for object detection tasks. Additionally, the number of points within the box will decrease for longer radial distances while collaboratively viewing the objects can potentially increase the sensing observation and thus provide better visual cues.

4 Tasks

In this section, we first present the V2X cooperative 3D object detection task with derived datasets as per the collaboration mode and ego perspective in Sect. 4.1, and then we introduce the evaluation metrics in Sect. 4.2. Afterwards, in Sect. 4.3, we introduce various benchmark methods and fusion strategies supported in our dataset.

4.1 V2X Cooperative 3D Object Detection

Scope: The V2X Cooperative 3D object detection aims to leverage multi-agent’s LiDAR point clouds to collaboratively perform 3D object detection. In our dataset, there are four collaborators including two infrastructure and two autonomous vehicles. Based on the V2X collaboration mode and ego agent type, we present four types of datasets: V2X-Real-VC, V2X-Real-IC, V2X-Real-V2V, and V2X-Real-I2I.

V2X-Real-VC: In V2X-Real-VC, the ego agent is fixed as the autonomous vehicle while the collaborators include both the infrastructure and vehicle. This setup is specifically designed for research of vehicle-centric V2X collaborations.

V2X-Real-IC: The infrastructure is chosen as the ego agent and the neighboring vehicles and infrastructure can collaborate with the ego infrastructure via sharing sensing observations. The final evaluation is conducted in the ego infrastructure side. This dataset is tailored for infrastructure-centric cooperative perception study.

V2X-Real-V2V: Only Vehicle-to-Vehicle collaboration is considered in this dataset. Additional scenarios collected in V2V corridors are used to supplement intersection scenarios with more diverse data distribution.

V2X-Real-I2I: In this dataset, Infrastructure-to-Infrastructure collaborations are studied, which is critical for intelligent transportation systems.

Contrary to existing works tailored for a single collaboration mode, the presented datasets have been meticulously crafted to cater to the diverse research interests of the broader V2X community.

4.2 Metrics

Ground Truth: During the training stage, a random agent will be selected as the ego agent while during the inference, the ego is fixed as per dataset categories. For example, in the V2X-Real-VC, the ego is fixed as one of the data collection vehicles while in the V2X-Real-IC, the ego is infrastructure. When the bounding boxes are not consistent across agents, we choose the ego agent’s annotation as the ground truth.

Evaluation: The evaluation is conducted in the range of -100 m to 100 m in x direction and -40 m to 40 m in y direction of the ego coordinate frame. We group the annotated 10 categories into three classes *i.e.* car, pedestrian and truck as per their bounding box size distribution. We calculate the Average Precision (AP) for each class based on the specified Intersection-over-Union (IoU) threshold, and a final mean Average Precision (mAP) is evaluated based on each category’s AP:

$$mAP = \frac{1}{C} \sum_{i=1}^C AP_i \quad (1)$$

where C is the class number. As our dataset contains a substantial number of pedestrians and large buses and the bounding box sizes can vary from less than 0.5 m (pedestrian) to over 20 m (bus), accurately predicting objects’ poses and dimensions is particularly challenging. Thus similar as KITTI-360 dataset [14], we adopt smaller IoU thresholds (IoU = 0.3, 0.5) for the AP calculation to faithfully reflect model’s perception capability.

4.3 Benchmark Methods

We provide benchmarks for all three fusion strategies in cooperative perception with SOTA fusion methods. Note that different from existing V2X 3D

Table 3. Benchmark results of SOTA cooperative perception methods for V2X-Real-VC, V2X-Real-IC, V2X-Real-V2V, and V2X-Real-I2I. All numbers in the table are represented in percentage format. For detection accuracy, Average Precision (AP) and mean Average Precision (mAP) for cars, pedestrians, and trucks are reported under IoU thresholds of 0.3 and 0.5.

Dataset	Models	AP _{car} @IoU		AP _{ped.} @IoU		AP _{truck} @IoU		mAP@IoU	
		0.3	0.5	0.3	0.5	0.3	0.5	0.3	0.5
V2X-Real-VC	No Fusion	38.7	35.9	25.5	13.1	20.2	14.5	28.2	21.2
	Late Fusion	46.1	43.1	28.3	11.8	19.8	14.0	31.4	23.0
	Early Fusion	51.1	47.6	31.6	16.0	32.5	23.6	38.4	29.1
	F-Cooper [2]	57.3	54.2	30.0	14.1	27.0	21.2	38.1	29.8
	AttFuse [34]	62.6	59.4	32.2	15.5	32.6	26.6	42.5	33.8
	V2X-ViT [33]	62.7	60.3	36.7	18.6	35.1	28.3	44.8	35.8
V2X-Real-IC	No Fusion	43.3	35.6	25.6	12.7	21.2	20.2	30.0	22.8
	Late Fusion	65.2	60.4	33.4	16.0	30.8	24.5	43.1	33.6
	Early Fusion	64.2	59.8	32.3	15.0	33.3	27.4	43.3	34.1
	F-Cooper [2]	49.7	43.0	31.0	15.3	31.9	21.1	37.5	26.5
	AttFuse [34]	70.4	67.3	37.5	17.0	42.9	31.3	50.3	38.5
	V2X-ViT [33]	64.2	56.5	37.8	19.2	35.6	28.8	45.9	34.8
V2X-Real-V2V	No Fusion	41.7	39.4	26.9	14.4	21.6	13.7	30.1	22.5
	Late Fusion	47.4	44.4	29.2	14.9	18.7	9.1	31.8	22.8
	Early Fusion	54.0	49.8	31.9	17.1	28.6	18.6	38.1	28.5
	F-Cooper [2]	42.7	40.3	27.7	14.0	25.6	18.6	32.0	24.3
	AttFuse [34]	58.6	55.3	30.1	15.4	28.9	21.7	39.2	30.8
	V2X-ViT [33]	59.0	56.3	37.4	20.7	42.9	35.0	46.5	37.3
V2X-Real-I2I	No Fusion	48.6	40.0	30.9	15.8	23.5	22.4	34.3	26.1
	Late Fusion	67.2	63.3	41.1	23.1	48.4	39.1	52.2	41.8
	Early Fusion	60.9	57.2	41.2	21.9	38.5	30.8	46.9	36.6
	F-Cooper [2]	71.5	65.5	49.3	27.5	50.0	40.7	56.9	44.6
	AttFuse [34]	73.5	69.5	42.8	20.5	53.2	39.4	56.5	43.1
	V2X-ViT [33]	77.3	68.8	54.4	30.5	56.2	51.5	62.7	50.3

object detection benchmarks [31, 35] where only single vehicle categories are detected and evaluated, we provide comprehensive benchmarks for all the annotated classes *i.e.* pedestrian, car, and truck, providing the first open cooperative perception framework for multi-class cooperative 3D object detection. Here we list the benchmarked fusion strategies and methods:

- **No Fusion:** Only ego agent’s LiDAR will be used to produce the 3D bounding boxes. It serves as the baseline.

- **Late Fusion:** Each agent first generates its own predictions and then shares the detection results with neighboring agents. The ego agent will receive these proposals and leverage non-maximum suppression (NMS) to produce consistent predictions.
- **Early Fusion:** The raw LiDAR point clouds will be shared for agents within the communication range. After receiving the neighboring agent’s LiDAR point clouds, the ego agent will transform LiDAR point clouds into the ego agent’s coordinate frame and aggregate all the LiDAR point clouds to produce a holistic view for visual reasoning.
- **Intermediate Fusion:** Each agent will first project its LiDAR to the ego agent’s coordinate frame and leverage the LiDAR backbone to extract Birds’ Eye View (BEV) features, which are then compressed and shared with the ego agent. The ego agent will leverage received multi-agent features to refine its own feature representations. In this work, we provide benchmarks for AttFuse [34], F-Cooper [2], and V2X-ViT [33].

5 Experiments

5.1 Implementation Details

We split the dataset into train/val/test with 23379, 2770, and 6850 frames respectively. For the detection models, we adopt PointPillar [9] as the LiDAR backbone. The cooperative perception framework is built upon OpenCOOD [34]. To enable multi-class cooperative perception, we extend the original single-class head to multi-class heads following OpenPCDet’s design [20]. All the models are trained with 80 epochs with a batch size of 2 and a learning rate of 0.001. Adam optimizer (decay weight $\lambda = 10^{-4}$) and multi-step learning rate scheduler ($\gamma = 0.1$, milestones = [10, 50]) are employed for optimization.

5.2 Benchmark Results

Table 3 summarizes the benchmark results of all six models for the four datasets. For all the datasets, cooperative methods outperform No Fusion baseline, demonstrating the great potential of V2X collaboration in enhancing the perception capabilities of individual agents. Among these cooperative methods, Intermediate Fusion methods typically yield more precise predictions compared to Late and Early Fusion strategies. Notably, across all three object categories, the models generally perform best in the car category, whereas the performance is comparatively lower for the pedestrian and truck categories. We argue this is due to the fact that truck type has a diverse dimension distribution (Fig. 6c) and pedestrian bounding boxes usually only contain a few sparse LiDAR points, posing challenges for the learning. Generally, intermediate fusion ranks first among three fusion strategies, and late fusion methods outperform No Fusion baselines while early fusion shows superior performance than late fusion.

6 Conclusion

In this work, we present the V2X-Real, the first large-scale real-world dataset for V2X cooperative perception. It encompasses 33K LiDAR frames, 171K RGB images, and an unprecedented 1.2 million annotated 3D bounding boxes, making it one of the largest V2X datasets of its kind with dense traffic flows. To facilitate a wide range of V2X collaboration research, we provide four sub-datasets including V2X-Real-VC, V2X-Real-IC, V2X-Real-V2V, and V2X-Real-I2I. We also present a comprehensive multi-class benchmark framework for cooperative 3D object detection and from the best of our knowledge, this framework is also the first open multi-class cooperative 3D object detection framework in the literature, which enables future multi-class cooperative perception research like cooperative perception for vulnerable road users. We will release our data and benchmark codes and hope our open-source efforts can inspire more researchers to investigate this new yet important field.

Future Work and Limitation: The current dataset comprises only LiDAR and camera data, lacking support for radar, which is crucial for developing low-cost, scalable autonomous driving solutions. In the future, we plan to further extend our sensor suits to low-cost sensors such as radar and low-beam LiDAR for studying scalable low-cost V2X solutions.

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