

Robustness-Aware 3D Object Detection in Autonomous Driving: A Review and Outlook

Ziying Song, Lin Liu, Feiyang Jia, Yadan Luo, Guoxin Zhang, Lei Yang, Li Wang, Caiyan Jia

Abstract—In the realm of modern autonomous driving, the perception system is indispensable for accurately assessing the state of the surrounding environment, thereby enabling informed prediction and planning. Key to this system is 3D object detection methods, that utilize vehicle-mounted sensors such as LiDAR and cameras to identify the size, category, and location of nearby objects. Despite the surge in 3D object detection methods aimed at enhancing detection precision and efficiency, there is a gap in the literature that systematically examines their resilience against environmental variations, noise, and weather changes. This study emphasizes the importance of robustness, alongside accuracy and latency, in evaluating perception systems under practical scenarios. Our work presents an extensive survey of camera-based, LiDAR-based, and multimodal 3D object detection algorithms, thoroughly evaluating their trade-off between accuracy, latency, and robustness, particularly on datasets like KITTI-C and nuScenes-C to ensure fair comparisons. Among these, multimodal 3D detection approaches exhibit superior robustness and a novel taxonomy is introduced to reorganize its literature for enhanced clarity. This survey aims to offer a more practical perspective on the current capabilities and constraints of 3D object detection algorithms in real-world applications, thus steering future research towards robustness-centric advancements.

Index Terms—Autonomous Driving, 3D Object Detection, Point clouds

I. INTRODUCTION

AUTONOMOUS driving systems, fundamental to the future of transportation, heavily rely on advanced perception, decision-making, and control technologies. These systems employ a range of sensors [1] such as camera, LiDAR and radar as depicted in Fig. 1, to effectively perceive the surrounding environment. This capability is crucial for recognizing road signs, detecting and tracking vehicles, and predicting pedestrian behavior, enabling safe operation amidst complex traffic conditions.

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The primary task of perception is to accurately understand the surrounding environment and minimize collision risks. This is where 3D object detection methods become essential. These approaches enable the autonomous systems to accurately identify objects in the vicinity, including their position, shape, and category [2]. Such detailed environmental perception enhances the system's ability to comprehend the driving context and make more informed decisions.

The advancement of autonomous driving technologies has spared a wave of research in 3D object detection, leading to the development of diverse and innovative methods. These approaches are typically categorized based on their input types, including Camera-based [3]–[17], [17]–[53], [53]–[100], Point Cloud-based [101]–[220], and multimodal methods [107], [136], [221]–[251]. The current landscape of 3D object detection methods is prolific, necessitating a comprehensive summarization to offer intriguing insights for the research community. While comprehensive, prior surveys [2], [252] often overlook the safety aspects of autonomous driving perception, particularly in terms of the system robustness against varying testing data after deployment.

In real-world testing scenarios, the conditions encountered can greatly differ from those during training. The environmental variability, sensor discrepancies or noise, and spatial misalignment can cause a shift in the input sensory data distribution, leading to a significant drop in detector performance [230], [233], [253], [254]. We identify and discuss three major factors critical for assessing the detection **robustness**: 1) **Environmental Variability**: The detection algorithm needs to perform well under different environmental conditions, including variations in lighting, weather, and seasonal changes. The algorithm should exhibit adaptability, ensuring that it does not fail due to changes in the environment. 2) **Sensor Noise**: This includes handling noise introduced by sensor malfunctions such as motion blur to camera. The algorithm must possess the capability to effectively manage hardware noise, ensuring accurate processing of input data. 3) **Misalignment**: In real-world scenarios, sensor calibration errors can complicate the synchronization of multimodal input data, causing misalignment due to external factors (e.g., uneven road surfaces) or internal factors (e.g., system clock misalignment). The algorithm should be fault-tolerant and may incorporate an elastic alignment to mitigate misalignment's impact on detection performance.

To ensure safe operation in varying test environments, assessing the robustness of 3D object detection algorithms is essential. They must maintain efficient, accurate, and reliable performance across diverse scenarios. In this survey, we

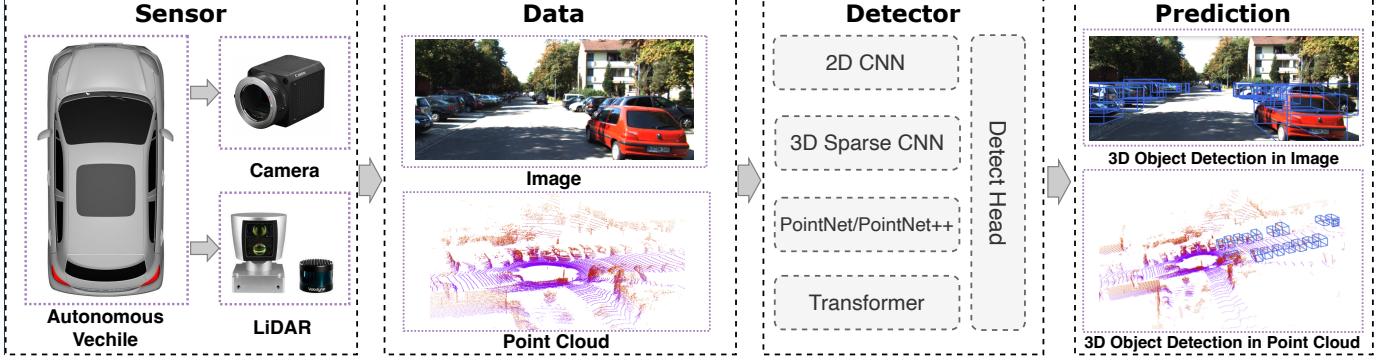


Fig. 1: An illustration of 3D object detection in autonomous driving scenarios with different sensors.

conduct extensive experimental comparisons among existing algorithms. Centered around 'Accuracy, Latency, Robustness', we delve into existing solutions, offering insightful guidance for practical deployment in autonomous driving.

- **Accuracy** Current research often prioritizes accuracy as a key performance metric. However, a deeper understanding of these methods' performance in complex environments and extreme weather conditions is needed to ensure real-world reliability. A more detailed analysis of false positives and false negatives is necessary for improvement.
- **Latency** Real-time capability is vital for autonomous driving. The latency of a 3D object detection method impacts the system's ability to make timely decisions, particularly in emergencies.
- **Robustness** Robustness refers to the system's stability under various conditions, including weather, lighting, sensory and alignment changes. Many existing evaluations may not fully consider the diversity of real-world scenarios, necessitating a more comprehensive adaptability assessment.

Through an in-depth analysis of extensive experimental results, with a focus on 'Accuracy, Latency, Robustness,' we have identified significant advantages in safety perception with multimodal 3D detection in safety perception. By integrating information from diverse sensors or data sources, the multimodal methods provide a richer and more diverse perception capability for autonomous driving systems, thereby enhancing the understanding and response to the surrounding environment. Our research provides practical guidance for the future deployment of autonomous driving technology. By discussing these key areas, we aim to align the technology more closely with real-world needs and enhance its societal benefits effectively.

The structure of this paper is organized as follows. First, we introduce the datasets and evaluation metrics for 3D object detection, with a particular focus on robustness in Section II. The subsequent sections systematically examine existing 3D object detection methods, including Camera-only (Section III), LiDAR-only (Section IV), and multimodal approaches (Section V). The paper concludes with a comprehensive summary of our findings VI.

TABLE I: Advantages and limitations of different modalities.

Type	Sensor	Hardware Cost(\$)	Advantages	Limitations
Image	Camera	$10^2\text{--}10^3$	+ The dense data format incorporates additional color and texture information.	- Missing depth information will be affected by light, weather, etc.
Point cloud	LiDAR	$10^4\text{--}10^5$	+ With accurate depth information less affected by light + larger field of view	- High computational cost for sparse and disordered point cloud data and no color information.
Multimodal	Camera, LiDAR	$10^4\text{--}10^5$	+ Simultaneous color and depth information	- Fusion methods can produce noise interference

II. DATASETS

Currently, autonomous driving systems primarily rely on sensors such as cameras, LiDAR, and radar, generating data in two modalities: point clouds and images. Based on these data types, existing public benchmarks predominantly manifest in three forms: Camera-only, LiDAR-only, and multimodal. Table I delineates the advantages and disadvantages of each of these three forms. Among them, there are many reviews [252], [269]–[275] providing a comprehensive overview of clean autonomous driving datasets as shown in II. The most notable ones include KITTI [255], nuScenes [256], and Waymo [262].

In recent times, the pioneering work on clean autonomous driving datasets has provided rich resources for 3D object detection. As autonomous driving technology transitions from breakthrough stages to practical implementation, we have undertaken some guided research to review the currently available robustness datasets systematically. We focus more on noisy scenarios and have systematically reviewed datasets related to the robustness of 3D detection. Many studies collect new datasets to evaluate model robustness under different conditions. Early research has explored camera-only approaches under adverse conditions [276], [277], with datasets notably small in scale and exclusively applicable to camera-only visual tasks rather than multimodal sensor stacks that include LiDAR. Subsequently, a series of multimodal datasets [278]–[281] focus on noise concerns. For instance, the GROUNDED dataset [278] focuses on ground-penetrating radar localization under varying weather conditions. Additionally, the ApolloScape

TABLE II: Public datasets for 3D object detection in autonomy driving.

Dataset	Year	Sensors	Data Size		Diversity		Scenes
			Frame	Annotation	Scenes	Category	
KITTI [255]	2012	Camera, LiDAR	15K	200K	50	3	Daytime and sunny days only
nuScenes [256]	2019	Camera, LiDAR, Radar	40K	1.4M	1000	10	Night and rainy days
Lyft L5 [257]	2019	Camera, LiDAR	46K	1.3M	366	9	Daytime and sunny days only
H3D [258]	2019	LiDAR	27K	1.1M	160	8	Daytime and sunny days only
Appollo [259]	2019	Camera, LiDAR	140K	-	103	27	Night and rainy days
Argoverse [260]	2019	Camera, LiDAR	46K	993K	366	9	Night and rainy days
A*3D [261]	2019	Camera, LiDAR	39K	230K	-	7	Night and severely obscured data
Waymo [262]	2020	Camera, LiDAR	230K	12M	1150	3	Night and rainy days
A2D2 [263]	2020	Camera, LiDAR	12.5K	43K	-	38	Daytime and sunny days only
PandaSet [264]	2020	Camera, LiDAR	14K	-	179	28	Daytime and sunny days only
KITTI-360 [265]	2020	Camera, LiDAR	80K	68K	11	19	Daytime and sunny days only
Cirrus [266]	2020	Camera, LiDAR	6285	-	12	8	Daytime and sunny days only
ONCE [267]	2021	Camera, LiDAR	15K	417K	-	5	Night and rainy days
OpenLane [268]	2022	Camera, LiDAR	200K	-	1000	14	Daytime and sunny days only

open dataset [280] incorporates LiDAR, camera, and GPS data, encompassing cloudy and rainy conditions and brightly lit scenarios.

Due to the prohibitive cost of collecting extensive noisy datasets from the real world, rendering the formation of large-scale datasets impractical, many studies have shifted their focus to synthetic datasets. ImageNet-C [282] is a seminal work in corruption robustness research, benchmarking classical image classification models against prevalent corruptions and perturbations. This line of research has subsequently extended to include robustness datasets tailored for 3D object detection in autonomous driving. Additionally, there are adversarial attacks [283]–[285] designed for studying the robustness of 3D object detection. However, these attacks may not exclusively concentrate on natural corruption, which is less prevalent in autonomous driving scenarios. To better emulate the distribution of noise data in the real world, several studies [253], [254], [286]–[289] have developed toolkits for robustness benchmarks. These benchmark toolkits [253], [254], [286]–[289] enable the simulation of various scenarios using clean autonomous driving datasets, such as KITTI [255], nuScenes [256], and Waymo [262]. Among them, Dong et al. [254] systematically designed 27 common corruptions in 3D object detection to benchmark the corruption robustness of existing detectors. By applying these corruptions comprehensively on public datasets, they established three corruption-robust benchmarks: KITTI-C, nuScenes-C, and Waymo-C. [254] denote model performance on the original validation set as AP_{clean} . For each corruption type c at each severity s , [254] adopt the same metric to measure model performance as $AP_{c,s}$. The corruption robustness of a model is calculated by averaging over all corruption types and severities as

$$\Delta P_{\text{cor}} = \frac{1}{|\mathcal{C}|} \sum_{c \in \mathcal{C}} \frac{1}{5} \sum_{s=1}^5 AP_{c,s}. \quad (1)$$

Where \mathcal{C} is the set of corruptions in evaluation, note that for different kinds of 3D object detectors, the set of corruptions can be different (e.g., [254] do not evaluate camera noises for LiDAR-only models). Thus, the results of ΔP_{cor} are not directly comparable between different kinds of models, and [254] performs a fine-grained analysis under each corruption.

[254] also calculates relative corruption error (RCE) by measuring the percentage of performance drop as

$$RCE_{c,s} = \frac{AP_{\text{clean}} - AP_{c,s}}{AP_{\text{clean}}}; RCE = \frac{AP_{\text{clean}} - AP_{\text{cor}}}{AP_{\text{clean}}}. \quad (2)$$

Unlike KITTI-C and Waymo-C, nuScenes-C primarily assesses performance using the mean Average Precision (mAP) and nuScenes Detection Score (NDS) computed across ten object categories. The mAP is determined using the 2D center distance on the ground plane instead of the 3D Intersection over Union (IoU). The NDS metric consolidates mAP with other aspects, such as scale and orientation, into a unified score. Analogous to KITTI-C, Ref. [254] denote the model's performance on the validation set as mAP_{clean} and NDS_{clean} , respectively. The corruption robustness metrics, mAP_{cor} and NDS_{cor} , are evaluated by averaging over all corruption types and severities. Additionally, Ref. [254] calculates the Relative Corruption Error (RCE) under both mAP and NDS metrics, similar to the formulation in Eq.2.

Additionally, some studies [283], [286], [290] examine robustness in single-modal contexts. For instance, Ref. [286] proposes a LiDAR-only benchmark that utilizes physical-aware simulation methods to simulate degraded point clouds under various real-world common corruptions. This benchmark, tailored for point cloud detectors, includes 1,122,150 examples across 7,481 scenes, covering 25 common corruption types with six severity levels. Moreover, Ref. [286] devise a novel evaluation metrics, including $CE_{AP}(\%)$ and mCE . Ref. [286] calculates corruption error (CE) to assess performance degradation based on Overall Accuracy (OA) by:

$$CE_{c,s}^m = OA_{\text{clean}}^m - OA_{c,s}^m, \quad (3)$$

where $OA_{c,s}^m$ is the overall accuracy of detector m under corruption c of severity level s (exclude "clean," i.e., severity level 0) and clean represent the clean data. For detection m , we can calculate the mean CE (mCE) for each detector by:

$$mCE^m = \frac{\sum_{s=1}^5 \sum_{c=1}^{25} CE_{c,s}^m}{5C}. \quad (4)$$

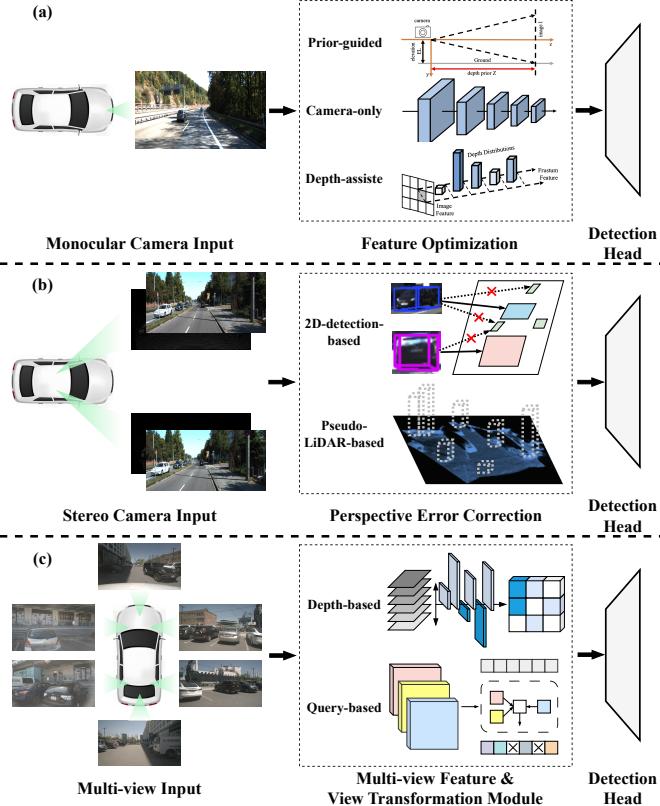


Fig. 2: Camera-only methods pipeline.

III. CAMERA-BASED 3D OBJECT DETECTION

In this section, we introduce the camera-based 3D object detection methods. Compared to LiDAR-based methods, the camera solution is more cost-effective and the generated image requires no complex preprocessing. Therefore, it is favored by many automotive manufacturers, particularly in the context of multi-view applications such as BEV (bird's-eye view) systems. Generally, as shown in Fig. 2, camera-based methods can be categorized into three types: (1) monocular, (2) stereo-based, and (3) multi-view (bird's-eye view). Due to the excellent cost-effectiveness of camera-based methods, there have been numerous reviews and investigations conducted to summarize and explore them. However, the majority of existing reviews on 3D object detection are limited to specific methodologies, with a predominant focus on accuracy. This survey aims to revisit the fundamental considerations of safety-perception deployment, redefining the discourse around existing categorizations, and exploring ‘Accuracy, Latency, and Robustness,’ as the core dimensions for an in-depth analysis of current methodologies. The objective is to provide additional insights to guide existing technologies.

A. Monocular 3D object detection

Monocular 3D object detection refers to performing 3D object detection using only one camera which aims to infer the 3D position, size, and orientation of target objects from a single image [274]. In recent years, monocular 3D object detection has gained increasing attention due to its advantages

of low cost, low power consumption, and ease of deployment in real-world applications. However, monocular methods face many challenges, owing to the insufficient 3D information in monocular pictures, such as accurately localizing the 3D position, handling occluded scenes, etc. Overcoming these challenges relies on leveraging depth information to supplement the missing 3D information in monocular images. Typically, most approaches employ depth estimation tasks to acquire depth information from images. However, monocular depth estimation is an ill-posed and highly challenging task, prompting researchers to dedicate significant efforts to optimize the accuracy and stability of depth estimation.

1) Prior-guided monocular 3D object detection: In recent years, prior-guided monocular methods [5], [6], [15]–[18], [20], [39], [43], [47], [49], [68], [291]–[296], [296]–[301] have continuously explored how to utilize the hidden prior knowledge of object shapes and scene geometry in images to address the challenges of monocular 3D object detection. This effective integration of prior knowledge is crucial for mitigating the uncertainty and ill-posed nature of monocular 3D object detection problems. By introducing pre-trained subnetworks or auxiliary tasks, prior knowledge can provide additional information or constraints to assist in the accurate localization of 3D objects and enhance detection precision and robustness.

Widely adopted prior knowledge in 3D objects includes object shapes [17], [293], [296], [297], [338], [339], geometric consistency [5], [6], [16], [43], [43], [300], [340], temporal constraints [47], [302], and segmentation information [20], [296]. Object shape provides insights into the appearance and structure of the object, aiding in more accurate inference of the spatial position and pose of the object. Geometric consistency knowledge assists the model in better understanding the relative positional relationships between objects in the scene, thereby improving detection consistency and robustness. Temporal constraints consider the continuity and stability of the object across different frames, providing vital clues for object detection. Additionally, leveraging segmentation information enables the model to better comprehend semantic information in the images, facilitating precise localization and identification of objects.

As a result, current works are dedicated to further exploring and utilizing prior knowledge to enhance the performance and robustness of monocular 3D object detection by integrating prior knowledge with deep learning approaches, thus driving continuous development and innovation in this field. The early algorithm Mono3D [50] first assumes the 3D object is on a fixed ground plane, and then uses the prior 3D shape of the vehicle to reconstruct the bounding box in 3D space. In subsequent work, Deep MANTA [292] uses keypoints and 3D CAD models to predict 3D objects. Pose-RCNN [341] learns viewpoint-specific subclass information from 3D CAD models to capture shape, viewpoint information, and potential occlusion patterns of objects. MonoPSR [49] generates 3D candidate frames for each object in the scene by using the fundamental relationships of the pinhole camera model and a well-established 2D object detector.

With a deeper understanding and application of prior knowl-

TABLE III: Camera-based 3D object detection methods.

Input Type	Keypoint	Methods
Monocular	Prior-guided: Direct regression using geometric prior knowledge	[5], [6], [15]–[18], [20], [39], [43], [47], [49], [68], [291]–[296], [296]–[301]
	Camera-only: uses the RGB image information captured by the monocular.	[5]–[7], [15], [21], [39], [48], [52], [53], [57], [65]–[68], [299], [301]–[305]
	Depth-assisted: extracting depth information via camera parallax.	[3], [4], [10], [36], [37], [45], [62], [69], [306], [307]
Stereo	2D-detection-based: Integrate 2D information about the target into the image.	[13], [24], [308]–[313]
	Pseudo-LiDAR-based: incorporate additional information from pseudo-LiDAR to simulate LiDAR depth.	[4], [14], [157], [314]
Multi-view	Depth-based: Convert 2D spatial features into 3D spatial features through depth estimation.	[25], [92], [93], [95], [96], [98], [100], [315]–[324]
	Query-based: Influenced by the transformer technology stack, there is a trend to explicitly or implicitly query Bird's Eye View (BEV) features.	[26], [87], [89]–[91], [94], [97], [99], [166], [319], [325]–[337]

edge, it is believed that significant progress will be achieved in monocular 3D object detection in the future, bringing breakthroughs and opportunities to the fields of computer vision and intelligent systems.

2) **Camera-only monocular 3D object detection:** Camera-only monocular 3D object detection [5]–[7], [15], [21], [39], [48], [52], [53], [57], [65]–[68], [299], [301]–[305] is a method that utilizes images captured by a single camera to detect and localize 3D objects. Camera-only monocular methods employ convolutional neural networks (CNNs) to directly regress 3D bounding box parameters from the images, enabling the estimation of the spatial dimensions and poses of objects in three dimensions. Drawing inspiration from the architectural design of 2D detection networks, this direct regression method can be trained in an end-to-end manner, facilitating holistic learning and inference for 3D objects. The unique challenge of monocular 3D object detection lies in inferring the 3D position, dimensions, and orientation of objects solely from a single image, without relying on additional depth maps or point cloud data. Consequently, the direct regression approach demonstrates practicality and broad applicability. By learning features from the images, convolutional neural networks can predict the 3D information of the objects. Through end-to-end training, the network gradually optimizes its parameters to enhance the accurate extraction of 3D information. This direct regression method streamlines the entire detection process and reduces reliance on supplementary information, thereby improving the algorithm's robustness and generalization capability. Nevertheless, monocular 3D object detection still presents challenges, such as occlusion, viewpoint variations, and changes in lighting conditions, which may impact the accuracy of 3D detection. The representative work Smoke [21] abandons the regression of 2D bounding boxes and predicts the 3D box for each detected target by combining the estimation of individual keypoints with the regression of 3D variables.

3) **Depth-assisted monocular 3D object detection:** Depth estimation plays a crucial role in depth-assisted monocular 3D object detection. To achieve more accurate monocular detection results, numerous studies [3], [4], [10], [36], [37], [45], [62], [69], [306], [307] leverage pre-trained auxiliary depth estimation networks. Specifically, the process begins by transforming monocular images into depth images using pre-

trained depth estimators, such as MonoDepth [342]. Subsequently, two primary methodologies are employed to handle depth images and monocular images.

Remarkable progress has been made in Pseudo-LiDAR detectors that use a pre-trained depth estimation network to generate Pseudo-LiDAR representations [60]–[62], [306]. However, there is a huge performance gap between Pseudo-LiDAR and LiDAR-based detectors because of the errors in image-to-LiDAR generation. Thus, Hong *et al.* [59] attempted to transfer deeper structural information from point clouds to assist monocular image detection. By leveraging the mean-teacher framework, they aligned the outputs of the LiDAR-based teacher model and the camera-based student model at both the feature-level and response-level, aiming to achieve cross-modal knowledge transfer. Such a depth-assisted monocular 3D object detection, by effectively integrating depth information, not only enhances detection accuracy but also extends the applicability of monocular vision to tasks involving 3D scene understanding.

B. Stereo-based 3D object detection

Stereo-based 3D object detection is designed to identify and localize 3D objects using a pair of stereo images. Leveraging the inherent capability of stereo cameras to capture dual perspectives, stereo-based methods excel in acquiring highly accurate depth information through stereo matching and calibration, a feature that sets them apart from monocular camera setups. Despite these advantages, stereo-based methods still face a considerable performance gap when compared to LiDAR-based counterparts. Furthermore, the realm of 3D object detection from stereo images remains relatively underexplored, with only limited research endeavors dedicated to this domain. Specifically, these approaches involve the utilization of image pairs captured from distinct viewpoints to estimate the 3D spatial depth of each object.

1) **2D-detection based methods:** Traditional 2D object detection frameworks can be modified to address stereo detection problems. Stereo R-CNN [23] employs an image-based 2D detector to predict 2D proposals, generating left and right regions of interest (RoIs) for the corresponding left and right images. Subsequently, in the second stage, it directly estimates

the parameters of 3D objects based on the previously generated RoIs. This paradigm has been widely adopted by follow works [13], [24], [308]–[313].

2) Pseudo-LiDAR based methods: The disparity map predicted from stereo images can be transformed into a depth map and further converted into a pseudo-LiDAR points. Consequently, similar to monocular detection methods, pseudo-LiDAR representations can also be employed in stereo-based 3D object detection approaches. These methods aim to enhance the disparity estimation in stereo matching to achieve more accurate depth predictions. Regarding the contribution of depth in 3D detection, Wang et al. [3] is a pioneer in introducing the Pseudo-LiDAR representation. This representation is generated by an image with a depth map, requiring the model to perform a depth estimation task to assist in detection. Subsequent work has followed this paradigm and made optimizations by introducing additional color information to augment pseudo point cloud [45], auxiliary tasks(instance segmentation [36], foreground and background segmentation [343] and domain adaptation [40]) and coordinate transform scheme [8], [306]. It is worth noting the insightful work proposed by Ma et al. called PatchNet [306]. Specifically, the authors challenges the conventional idea of leveraging the pseudo-LiDAR representation for monocular 3D object detection. By encoding 3D coordinates for each pixel, PatchNet can attain a comparable monocular detection result without pseudo-LiDAR representation. This observation indicates that the power of the pseudo LiDAR representation stems from the coordinate transformation rather than the point cloud representation itself.

C. Multi-view 3D object detection

Recently, multi-view 3D object detection has demonstrated superior accuracy and robustness compared to the aforementioned monocular and stereo 3D object detection approaches. In contrast to LiDAR-based 3D object detection, the latest panoramic Bird’s Eye View (BEV) approaches eliminate the need for high-precision maps, elevating the detection from 2D to 3D. This advancement has led to significant developments in multi-view 3D object detection. In comparison to previous reviews [1], [2], [242], [252], [269]–[275], [344]–[350], there has been extensive research on effectively leveraging multi-view images for 3D object detection. In multi-camera 3D object detection, a key challenge lies in recognizing the same object across different images and aggregating object features from multiple view inputs. The current approach involves uniformly mapping multi-view to the Bird’s Eye View (BEV) space, which is a common practice. Therefore, multi-view 3D object detection, also referred to as BEV-camera-only 3D object detection, revolves around the core challenge of unifying 2D views into the BEV space. Based on different spatial transformations, this can be categorized into two main methods: one approach is depth-based methods [25], [92], [93], [95], [96], [98], [100], [315]–[324], represented by the LSS [316], also known as the 2D to 3D transformation. The other approach is query-based methods [26], [87], [89]–[91], [94], [97], [99], [166], [319], [325]–[337] represented by the DETR3D [88], achieving a query from 3D to 2D.

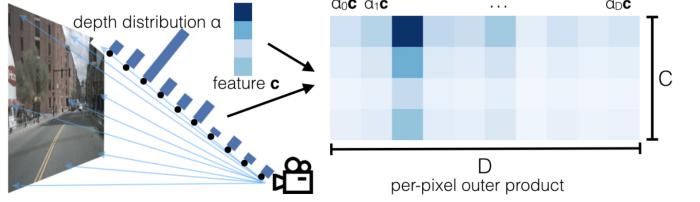


Fig. 3: LSS [316] “lifts” 2D space to 3D space through depth distribution.

1) Depth-based Multi-view methods: The direct transformation from 2D to BEV space poses a significant challenge. As shown in Fig. 3, LSS [316] was the first to propose a depth-based method, utilizing 3D space as an intermediary. This approach involves initially predicting the grid depth distribution of 2D features and then elevating these features to voxel space. This method holds promise for more effectively achieving the transformation from 2D to BEV space. Following LSS [316], CaDDN [52] adopted a similar depth representation approach. It employed a network structure akin to LSS, primarily for predicting categorical depth distribution. By compressing voxel-space features to BEV space, it performed the final 3D detection. It is worth noting that CaDDN is not part of multi-view 3D object detection, but rather single-view 3D object detection, which has influenced subsequent research on depth. The main distinction between LSS [316] and CaDDN [52] lies in CaDDN’s use of actual ground truth depth values to supervise its prediction of categorical depth distribution, resulting in an outstanding depth network capable of more accurately extracting 3D information from 2D space. This line of research has sparked a series of subsequent studies, such as BEVDet [315], its temporal version BEVDet4D [95], and BEVDepth [25]. These studies are of great significance in advancing the transformation from 2D to 3D space and enabling more accurate object detection in the BEV space, providing valuable insights and directions for the relevant field’s development. Furthermore, some studies have addressed the issue of insufficient depth solely by encoding height information. These studies have found that with increasing distance, the depth disparity between the car and the ground rapidly diminishes [100], [317].

2) Query-based Multi-view methods: Under the influence of Transformer [351]–[354] technology, query-based Multi-view methods retrieve 2D spatial features from 3D space. Inspired by Tesla’s perception system, DETR3D [88] introduces 3D object queries to address the aggregation of multi-view features. It accomplishes this by clipping image features from different perspectives and projecting them into 2D space using learned 3D reference points, thus obtaining image features in the Bird’s Eye View (BEV) space. Query-based Multi-view methods, contrary to Depth-based Multi-view methods, acquire sparse BEV features by employing a reverse querying technique, fundamentally impacting subsequent query-based developments [26], [87], [89]–[91], [94], [97], [99], [166], [319], [325]–[337]. However, due to the potential inaccuracies associated with explicit 3D reference points, PETR [89], as shown in Fig. 4, influenced by DETR [355] and DETR3D [88],

adopts an implicit positional encoding method for constructing the BEV space, influencing subsequent works [90], [336]. Meanwhile, some methods [225], [356] do not explicitly construct Bird's Eye View (BEV) features.

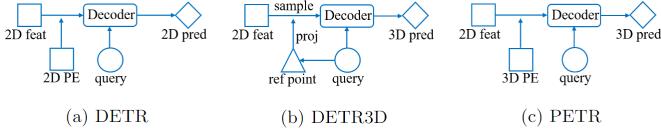


Fig. 4: Comparison of DETR [355], DETR3D [88], and PETR [89].

D. Analysis: Accuracy, Latency, Robustness

Currently, the 3D object detection solutions based on Bird's Eye View (BEV) perception are rapidly advancing. Despite the existence of numerous reviews [1], [2], [242], [252], [269]–[275], [344]–[350], a comprehensive review of this field remains inadequate. It is noteworthy that Shanghai AI Lab and SenseTime Research have provided a thorough review [357] of the technical roadmap for BEV solutions. However, unlike existing reviews [1], [2], [242], [252], [269]–[275], [344]–[350], which primarily focus on the technical roadmap and the current state of the art, we consider crucial aspects such as autonomous driving safety perception. Following an analysis of the technical roadmap and the current state of development for camera-based solutions, we intend to base our discussion on the foundational principles of ‘Accuracy, Latency, Robustness.’ We will integrate the perspectives of safety perception to guide the practical implementation of safety perception in autonomous driving.

1) **Accuracy:** Accuracy is a focal point of interest in the majority of research articles and reviews and is indeed of paramount importance. While accuracy can be reflected through AP (average precision), considering AP alone for comparison may not provide a comprehensive view, as different methodologies may exhibit substantial differences due to differing paradigms. As shown in Fig. 5 (a), we selected 10 representative methods (including classic and latest research) for comparison, and it is evident that there are significant metric disparities between monocular 3D object detection [11], [18], [21], [54]–[56], [75], [76], [301], [305] and stereo-based 3D object detection [13], [24], [28], [310], [358]–[363]. The current scenario indicates that the accuracy of monocular 3D object detection is far lower than that of stereo-based 3D object detection. Stereo-based 3D object detection leverages the capture of images from two different perspectives of the same scene to obtain depth information. The greater the baseline between cameras, the wider the range of depth information captured. As shown in Fig. 5 (b), there existed monocular 3D object detection methods [7], [65], [67], [69], [364] on the nuScenes dataset 2021 ago, but no related research on Stereo-based 3D object detection. Starting from 2021, monocular methods have gradually been supplanted by multi-view (bird's-eye-view perception) 3D object detection Multi-view [25], [26], [88]–[90], [329], [330], [336], [337], [365], leading to a significant improvement in mAP. The emergence of the novel

bird's-eye-view paradigm and the increase in sensor quantity have had a substantial impact on mAP. It can be observed that initially the disparity between DD3D [69] and DETR3D [88] was not prominent, but with the continuous enhancement of multi-view 3D object detection, particularly with the advent of novel works such as Far3D [337], the gap has widened. In other words, at present, Camera-xonly 3D object detection methods on multi-camera datasets like nuScenes [256] are predominantly based on bird's-eye-view perception. If we consider accuracy solely from this single dimension, the increase in sensor quantity has led to a significant improvement in accuracy metrics (including mAP, NDS, AP, etc.).

2) **Latency:** Latency holds paramount importance in the realm of autonomous driving. It refers to the time required for a system to react to input signals, encompassing the entire process from sensor data acquisition to system decision-making and execution of actions. In autonomous driving, stringent requirements are imposed on latency, as any form of delay can lead to severe consequences. The following aspects underscore the importance of latency in autonomous driving.

- **Real-time responsiveness** Autonomous driving systems need to demonstrate exceptional real-time responsiveness. Timely decision-making and actions are crucial for collision avoidance, adapting to traffic changes, and ensuring vehicle safety.
- **Safety** High latency may result in the system's inability to timely detect and respond to potential hazardous situations. Timely responses are a key factor in ensuring driving safety.
- **User Experience** For passengers and other road users, a smooth and coherent driving experience is crucial. High latency may lead to an uncomfortable driving experience or even induce anxiety.
- **Interactivity** Autonomous vehicles need to interact with other vehicles, pedestrians, and infrastructure. Low latency ensures timely communication and coordination, thereby enhancing the overall efficiency of the transportation system.
- **Emergency Response** In emergency situations, such as the sudden appearance of obstacles or rapid changes in traffic conditions, the system needs to react quickly to mitigate potential dangers.

In the field of 3D object detection, Latency (Frames Per Second, FPS) and Accuracy are critical metrics for assessing the performance of algorithms. As shown in Fig. 6 (a), the chart for monocular and stereo 3D object detection illustrates the relationship between Average Precision (AP) at the moderate difficulty level of the KITTI dataset and FPS. Fig. 6 (b) shows the relationship between the nuScenes Detection Score (NDS) and FPS for monocular and multi-view 3D object detection. These FPS were obtained using a NVIDIA A100 graphics card, while the performance metrics AP and NDS are derived from the original papers.

Specifically, monocular-based 3D object detection, relying on data from a single camera, typically has lower computational requirements, thus achieving a higher FPS. However, due to the absence of depth information, its accuracy is often inferior to that of stereo or multi-view systems. Stereo-

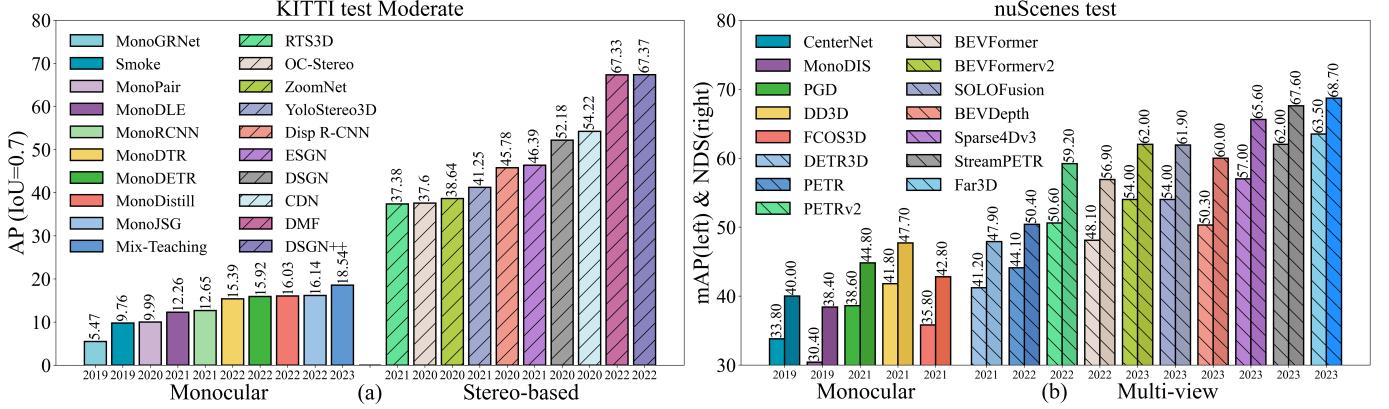


Fig. 5: (a) AP_{3D} comparison of monocular-based [11], [18], [21], [54]–[56], [75], [76], [301], [305] methods and Stereo-based [13], [24], [28], [310], [358]–[363] methods on KITTI moderate dataset. (b) The mAP (left) and NDS (right) comparison of monocular-based methods [7], [65], [67], [69], [364] methods and Multi-view methods [25], [26], [88]–[90], [329], [330], [336], [337], [365] on the nuScenes test dataset.

based 3D object detection, utilizing disparity information from images captured by dual cameras, enhances the accuracy of depth estimation but also introduces greater computational complexity, which may reduce FPS. Multi-view detection merges data from several cameras to provide richer scene information, which further improves accuracy. This method requires more extensive data processing, hence demanding greater computational power and algorithmic optimization to sustain a reasonable FPS level. Notably, there are no stereo-based 3D object detection methods represented on the nuScenes, with the monocular method FCOS3D [65] being particularly emblematic as it was introduced in 2021. With time and optimization, multi-view 3D object detection has rapidly developed in terms of both accuracy and latency.

In conclusion, for the realization of safe autonomous driving, 3D object detection algorithms must balance between Latency and Accuracy. While monocular detection is fast, it lacks precision, conversely, stereo and multi-view methods are accurate but slower. Future research should not only maintain high precision but also place greater emphasis on increasing FPS and reducing Latency to meet the dual requirements of real-time responsiveness and safety in autonomous driving.

3) Robustness: Robustness constitutes a pivotal factor in the safety perception of autonomous driving, representing a topic of significant attention that has been previously overlooked in comprehensive reviews. In the current meticulously designed clean datasets and benchmarks such as KITTI [255], nuScenes [256], and Waymo [262], this aspect is not commonly addressed. Presently, research works [253], [254], [287], [288], [388]–[390] like RoboBEV [253], Robo3D [288] on 3D object detection incorporate considerations of robustness, exemplified by factors such as sensor misses, as illustrated in Fig. 7. They have adopted a methodology involving the introduction of disturbances in datasets relevant to 3D object detection to assess robustness. This includes the introduction of various types of noise, such as variations in weather conditions, sensor malfunctions, motion disturbances, and object-related perturbations, aimed at unraveling the dis-

tinct impacts of different noise sources on the model. Typically, most papers investigating robustness conduct evaluations by introducing noise to the validation sets of clean datasets, such as KITTI [255], nuScenes [256], and Waymo [262]. Additionally, we highlight findings from Ref. [254], where KITTI-C [254], and nuScenes-C [254], are emphasized as examples to illustrate the results of Camera-Only 3D object detection methods. Tables IV and V provide an overall comparison, revealing that, in general, Camera-Only methods are less robust compared to LiDAR-Only and multi-model fusion methods. They are highly susceptible to various types of noise. In KITTI-C, three representative works—SMOKE [21], PGD [67], and ImVoxelNet [391]—show consistently lower overall performance and reduced robustness to noise. In nuScenes-C, noteworthy methods such as DETR3D [88] and BEVFormer [26] exhibit greater robustness compared to FCOS3D [65] and PGD [67], suggesting that as the number of sensors increases, overall robustness improves. In conclusion, future Camera-Only methods need to consider not only cost factors and Accuracy metrics (mAP, NDS, etc.) but also factors related to safety perception and robustness. Our analysis aims to provide valuable insights for the safety of future autonomous driving systems.

IV. LiDAR-BASED 3D OBJECT DETECTION

In this section, we introduce LiDAR-based 3D object detection which utilizes point clouds as input data and extracts point cloud features to predict 3D objects. The point cloud (PC) is a set of points in Euclidean space, which can be expressed as $L_{point} \in R^{N \times (3+C)}$, where 3 and C are the coordinate (x, y, z -axis) and extra feature (reflection intensity in general) respectively, and N is the number of points. The characteristics of the points are the following: (1) **Sparsity**. The point clouds are formally distributed discretely, and the location and distance of each point are irregularly distributed in 3D space. (2) **Invariance**. For example, when different sensors find an object, the order in which the points are collected is disparate. It poses that the network is hard to fit well because

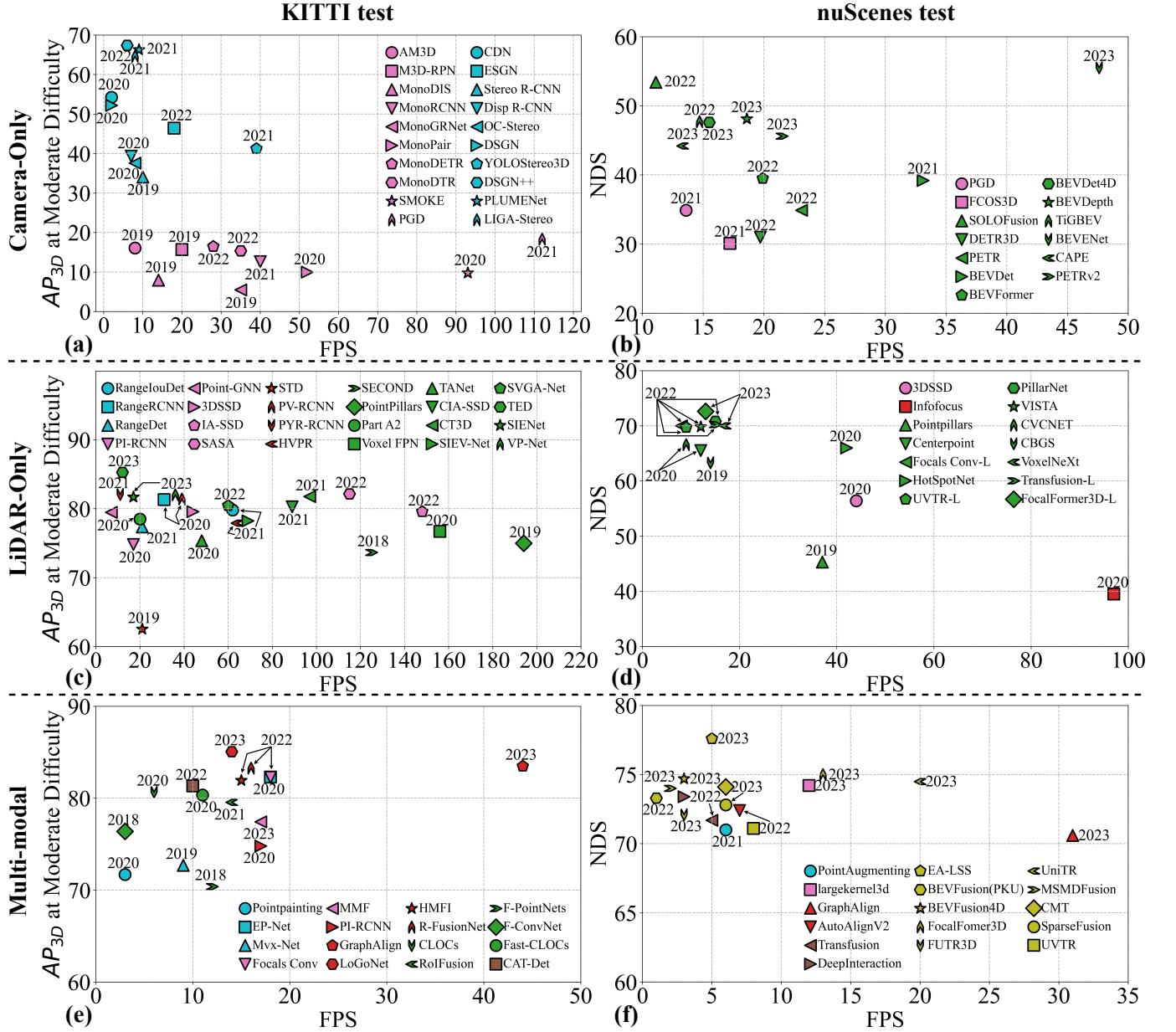


Fig. 6: (a) The FPS and AP_{3D} comparison of monocular-based [7], [15], [18], [21], [45], [56], [67], [76], [301], [305] methods and Stereo-based [13], [23], [24], [28], [309], [358], [362], [363], [366], [367] methods on the KITTI test dataset. (b) The FPS and NDS comparison of monocular-based [65], [67] methods and Multi-view [25], [26], [88]–[90], [95], [315], [321], [330], [331], [368] methods on the nuScenes test dataset. (c) The FPS and AP_{3D} comparison of view-based methods [173], [175], [176], Point-based methods [105], [110], [186], [369], [370], PV-based methods [165], [168], [251], [371] and Voxel-based methods [101], [109], [115], [118], [121], [134], [139], [147], [151], [372]–[374] on the KITTI test dataset. (d) The FPS and NDS comparison of Point-based methods [105], PV-based methods [167] and Voxel-based methods [112], [118], [125], [136], [154], [183], [201], [220], [230], [232], [364], [375] on the nuScenes test dataset. (e) The FPS and AP_{3D} comparison of Point-Projection-based methods [222], [226], [376], Feature-Projection-based methods [232], [377], Auto-Projection-based methods [233], [243], [247], [369], [378], Decision-Projection-based methods [196], [379]–[382] and Query-Learning-based methods [245] on the KITTI test dataset. (f) The FPS and NDS comparison of Point-Projection-based methods [383], Feature-Projection-based methods [129], Auto-Projection-based methods [233], [384], Query-Learning-based methods [230], [237] and Unified-Feature-based methods [136], [223], [225], [228], [231], [356], [375], [385]–[387] on the nuScenes test dataset.

TABLE IV: Comparison with SOTA methods on **KITTI-C validation** set. The results are evaluated based on the **car** class with AP of R_{40} at **moderate** difficulty. The best one is highlighted in **bold**. ‘RCE’ denotes Relative Corruption Error from Ref. [254].

Corruptions		LiDAR-Only						Camera-Only			multimodal			
		SECOND	[†] PointPillars	[†] PointRCNN	[†] PV-RCNN	[†] Part-A ²	[†] 3DSSD	[†] SMOKE	[†] PGD	[†] ImVoxelNet	EPNet	[†] Focals	Conv	[†] LoGoNet
None(AP_{clean})		81.59	78.41	80.57	84.39	82.45	80.03	7.09	8.10	11.49	82.72	85.88	86.07	91.95
Weather	Snow	52.34	36.47	50.36	52.35	42.70	27.12	2.47	0.63	0.22	34.58	34.77	51.45	51.17
	Rain	52.55	36.18	51.27	51.58	41.63	26.28	3.94	3.06	1.24	36.27	41.30	55.80	50.57
	Fog	74.10	64.28	72.14	79.47	71.61	45.89	5.63	0.87	1.34	44.35	44.55	67.53	75.63
	Sunlight	78.32	62.28	62.78	79.91	76.45	26.09	6.00	7.07	10.08	69.65	80.97	75.54	63.62
Sensor	Density	80.18	76.49	80.35	82.79	80.53	77.65	-	-	-	82.09	84.95	83.68	80.70
	Cutout	73.59	70.28	73.94	76.09	76.08	73.05	-	-	-	76.10	78.06	77.17	75.18
	Crosstalk	80.24	70.85	71.53	82.34	79.95	46.49	-	-	-	82.10	85.82	82.00	75.67
	Gaussian (L)	64.90	74.68	61.20	65.11	60.73	59.14	-	-	-	60.88	82.14	61.85	63.16
	Uniform (L)	79.18	77.31	76.39	81.16	77.77	74.91	-	-	-	79.24	85.81	82.94	70.74
	Impulse (L)	81.43	78.17	79.78	82.81	80.80	78.28	-	-	-	81.63	85.01	84.66	80.50
	Gaussian (C)	-	-	-	-	-	-	1.56	1.71	2.43	80.64	80.97	84.29	82.55
	Uniform (C)	-	-	-	-	-	-	2.67	3.29	4.85	81.61	83.38	84.45	82.56
Motion	Moving Obj.	52.69	50.15	50.54	54.60	79.57	77.96	1.67	2.64	5.93	55.78	49.14	14.44	32.28
	Motion Blur	-	-	-	-	-	-	3.51	3.36	4.19	74.71	81.08	84.52	82.58
Object	Local Density	75.10	69.56	74.24	77.63	79.57	77.96	-	-	-	76.73	80.84	78.63	78.73
	Local Cutout	68.29	61.80	67.94	72.29	75.06	73.22	-	-	-	69.92	76.64	64.88	71.01
	Local Gaussian	72.31	76.58	69.82	70.44	77.44	75.11	-	-	-	75.76	82.02	55.66	72.85
	Local Uniform	80.17	78.04	77.67	82.09	80.77	78.64	-	-	-	81.71	84.69	79.94	79.61
	Local Impulse	81.56	78.43	80.26	84.03	82.25	79.53	-	-	-	82.21	85.78	84.29	82.07
	Shear	41.64	39.63	39.80	47.72	37.08	26.56	1.68	2.99	1.33	41.43	45.77	-	-
	Scale	73.11	70.29	71.50	76.81	75.90	75.02	0.13	0.15	0.33	69.05	69.48	-	-
	Rotation	76.84	72.70	75.57	79.93	75.50	76.98	1.11	2.14	2.57	74.62	77.76	-	-
Alignment	Spatial	-	-	-	-	-	-	-	-	-	35.14	43.01	-	-
Average(AP_{cor})		70.45	65.48	67.74	72.59	69.92	60.55	2.68	2.42	3.05	67.81	71.87	80.93	85.66
RCE (%) ↓		13.65	16.49	15.92	13.98	15.20	24.34	62.20	70.12	73.46	22.03	18.02	5.97	6.84

†: Results from Ref. [254].

* denotes the result of our re-implementation.

TABLE V: Comparison with SOTA methods on **nuScenes-C validation** set with mAP. ‘D.I.’ refers to DeepInteraction [237]. The best one is highlighted in **bold**. ‘RCE’ denotes Relative Corruption Error from Ref. [254].

Corruptions		LiDAR-Only			Camera-Only			multimodal				
		PointPillars [†]	SSN [†]	CenterPoint [†]	FCOS3D [†]	PGD [†]	DETR3D [†]	BEVFormer [†]	FUTR3D [†]	TransFusion [†]	BEVFusion [†]	D.I.*
None(AP_{clean})		27.69	46.65	59.28	23.86	23.19	34.71	41.65	64.17	66.38	68.45	69.90
Weather	Snow	27.57	46.38	55.90	2.01	2.30	5.08	5.73	52.73	63.30	62.84	62.36
	Rain	27.71	46.50	56.08	13.00	13.51	20.39	24.97	58.40	65.35	66.13	66.48
	Fog	24.49	41.64	43.78	13.53	12.83	27.89	32.76	53.19	53.67	54.10	54.79
	Sunlight	23.71	40.28	54.20	17.20	22.77	34.66	41.68	57.70	55.14	64.42	64.93
Sensor	Density	27.27	46.14	58.60	-	-	-	-	63.72	65.77	67.79	68.15
	Cutout	24.14	40.95	56.28	-	-	-	-	62.25	63.66	66.18	66.23
	Crosstalk	25.92	44.08	56.64	-	-	-	-	62.66	64.67	67.32	68.12
	FOV lost	8.87	15.40	20.84	-	-	-	-	26.32	24.63	27.17	42.66
	Gaussian (L)	19.41	39.16	45.79	-	-	-	-	58.94	55.10	60.64	57.46
	Uniform (L)	25.60	45.00	56.12	-	-	-	-	63.21	64.72	66.81	67.42
	Impulse (L)	26.44	45.58	57.67	-	-	-	-	63.43	65.51	67.54	67.41
	Gaussian (C)	-	-	-	3.96	4.33	14.86	15.04	54.96	64.52	64.44	66.52
Motion	Compensation	3.85	10.39	11.02	-	-	-	-	31.87	9.01	27.57	39.95
	Moving Obj.	19.38	35.11	44.30	10.36	10.47	16.63	20.22	45.43	51.01	51.63	64.74
Object	Motion Blur	-	-	-	10.19	9.64	11.06	19.79	55.99	64.39	64.74	65.45
	Local Density	26.70	45.42	57.55	-	-	-	-	63.60	65.65	67.42	67.71
	Local Cutout	17.97	32.16	48.36	-	-	-	-	61.85	63.33	63.41	65.19
	Local Gaussian	25.93	43.71	51.13	-	-	-	-	62.94	63.76	64.34	64.75
	Local Uniform	27.69	46.87	57.87	-	-	-	-	64.09	66.20	67.58	66.44
	Local Impulse	27.67	46.88	58.49	-	-	-	-	64.02	66.29	67.91	67.86
	Shear	26.34	43.28	49.57	17.20	16.66	17.46	24.71	55.42	62.32	60.72	-
	Scale	27.29	45.98	51.13	6.75	6.57	12.02	17.64	55.42	62.32	60.72	-
Alignment	Rotation	27.80	46.93	54.68	17.21	16.84	27.28	33.97	59.64	63.36	65.13	-
	Spatial	-	-	-	-	-	-	-	63.77	66.22	68.39	-
Average(AP_{cor})		23.42	40.37	49.81	10.26	10.68	18.60	22.79	56.99	58.73	61.03	62.92
RCE(%) ↓		15.42	13.46	15.98	57.00	53.95	46.89	46.41	11.45	11.52	10.84	11.09

†: Results from Ref. [254].

* denotes the result of our re-implementation.

the points are all different. Therefore, putting CNN networks on point clouds causes information loss and makes it hard to train, and it usually requires preprocessing operations on point clouds to solve such problems.

Compared to camera-based methods, LiDAR captures pre-

cise 3D information, enabling LiDAR-based approaches to achieve higher detection accuracy and robustness, especially in extreme weather conditions [254]. Because in comparison to optical radiation, the laser beams emitted by LiDAR systems

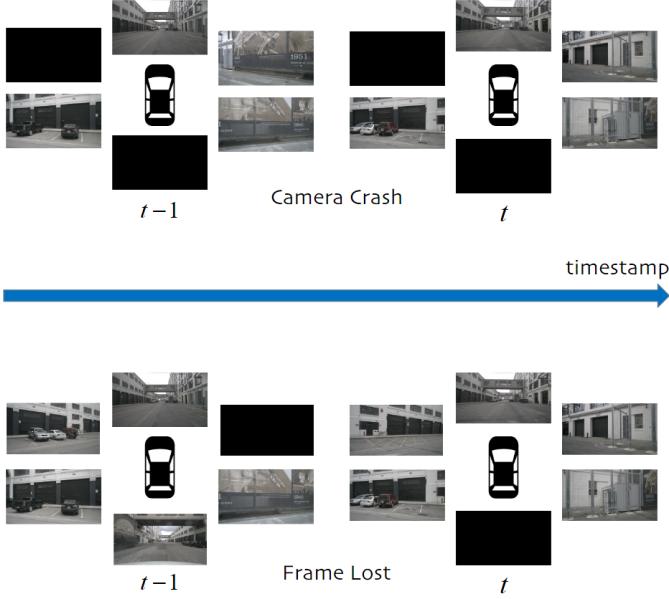


Fig. 7: Corruption Examples in the RoboBEV [253] Benchmark: Simulating Camera Malfunction.

can penetrate certain weather disturbances, such as raindrops and haze, with slight interference. However, the high cost of LiDAR remains one of the main barriers to large-scale adoption of LiDAR-based methods. In addition, the lack of semantic information leads to poor classification performance of LiDAR-based methods. Generally, as shown in Fig. 8, LiDAR-based methods can be categorized into four types: (1) view-based 3D object detection, (2) voxel-based 3D object detection, (3) point-based 3D object detection, (4) point-voxel-based 3D object detection. In contrast to previous reviews [1], [2], [242], [252], [269]–[275], [344]–[350], our survey extends beyond the conventional classifications of LiDAR-based methods. We adopt a more foundational idea to class LiDAR-based methods based on their core **data representations** (such as 2D Bird’s Eye View (BEV), Voxel, Pillar, etc.) and underlying **model structure** (base models including Convolutional Neural Networks (CNN), Transformers, PointNet, and others). This methodological restructuring aims to provide a comprehensive understanding of the technological paradigms at the heart of LiDAR-based methods, analyzing and classifying these systems from a more essential, technical lineage perspective.

A. View-based 3D object detection

The core idea of the view-based methods is to transform point clouds into pseudo-image representations from a bird’s-eye view (BEV) or range view by plane [392], cylindrical [393], or spherical [394] projections. In these representations, each pixel contains 3D spatial information rather than RGB values. Due to the dense representation of pseudo-images, traditional or specialized 2D convolutions can be seamlessly applied to range images, making the feature extraction process highly efficient. However, compared to other LiDAR-based methods, detection using range views is more susceptible to occlusion and scale variations. Hence, some

methods [173], [175] transform the data representation from the range view to the bird’s eye view (BEV). Furthermore, due to the projection of distant 3D spatial points becoming adjacent in the 2D image, traditional 2D CNN feature extraction operators may become less effective. In response to this issue, some methods [174], [176], [395] have specifically redesigned feature extraction operators for range images. Based on the different data representation views, the view-based methods can be divided into two categories: 1) **Range View**, 2) **BEV View**.

1) **Range View**: Due to the sparsity of point cloud data, projecting it directly onto an image plane results in a sparse 2D point map. Therefore, most methods [173]–[176], [396], [397] project the point cloud into the cylinder coordinate to generate a dense front-view representation by using the following projection function:

$$\begin{aligned} \theta &= \text{atan}2(y, x), \\ \phi &= \arcsin(z / \sqrt{x^2 + y^2 + z^2}), \\ r &= \lfloor \theta / \Delta\theta \rfloor, \\ c &= \lfloor \phi / \Delta\phi \rfloor, \end{aligned} \quad (5)$$

where $p = (x, y, z)^T$ denotes a 3D point and (r, c) denotes the 2D map position of its projection. θ and ϕ denote the azimuth and elevation angle when observing the point. $\Delta\theta$ and $\Delta\phi$ are the average horizontal and vertical angle resolution between consecutive beam emitters, respectively.

VeloFCN [393] is an influential work which first introduced the projection method in cylindrical coordinates. Then, it is followed by [173]–[176]. LaserNet [396] utilized DLA-Net [398] to obtain multi-scale features and detect 3D objects from this representation. Inspired by LaserNet, some works borrow the models in 2D object detection to handle range images, e.g. U-Net [399] is applied in [173], [397], [400], RPN [401] is employed in [173], [174] and FPN [402] is leveraged in [176]. Considering the limitations of traditional 2D CNNs in extracting features from range images, some works resort to novel operators, including range dilated convolutions [174], graph operators [395], and meta-kernel convolutions [176]. Furthermore, some works have focused on addressing occlusion and scale variation issues in range view. Specifically, these methods [173], [175] construct feature transformation structures from range view to point view and from point view to BEV view to convert range features into the BEV perspective.

2) **BEV View**: Comparison to range view detection, BEV-based detection is more robust to occlusion and scale variation challenges. Hence, feature extraction from the range view and object detection from the bird’s eye view becomes the most practical solution to range-based 3D object detection.

The bird’s eye view representation is encoded by height, intensity and density. The point cloud is discretized into a regular 2D grid. To encode more detailed height information, the point cloud is evenly divided into M slices, resulting in M height maps where each grid cell stores the maximum height value of the point cloud. The intensity feature represents the reflectance value of the point within each grid cell. And the point cloud density indicates the number of points in

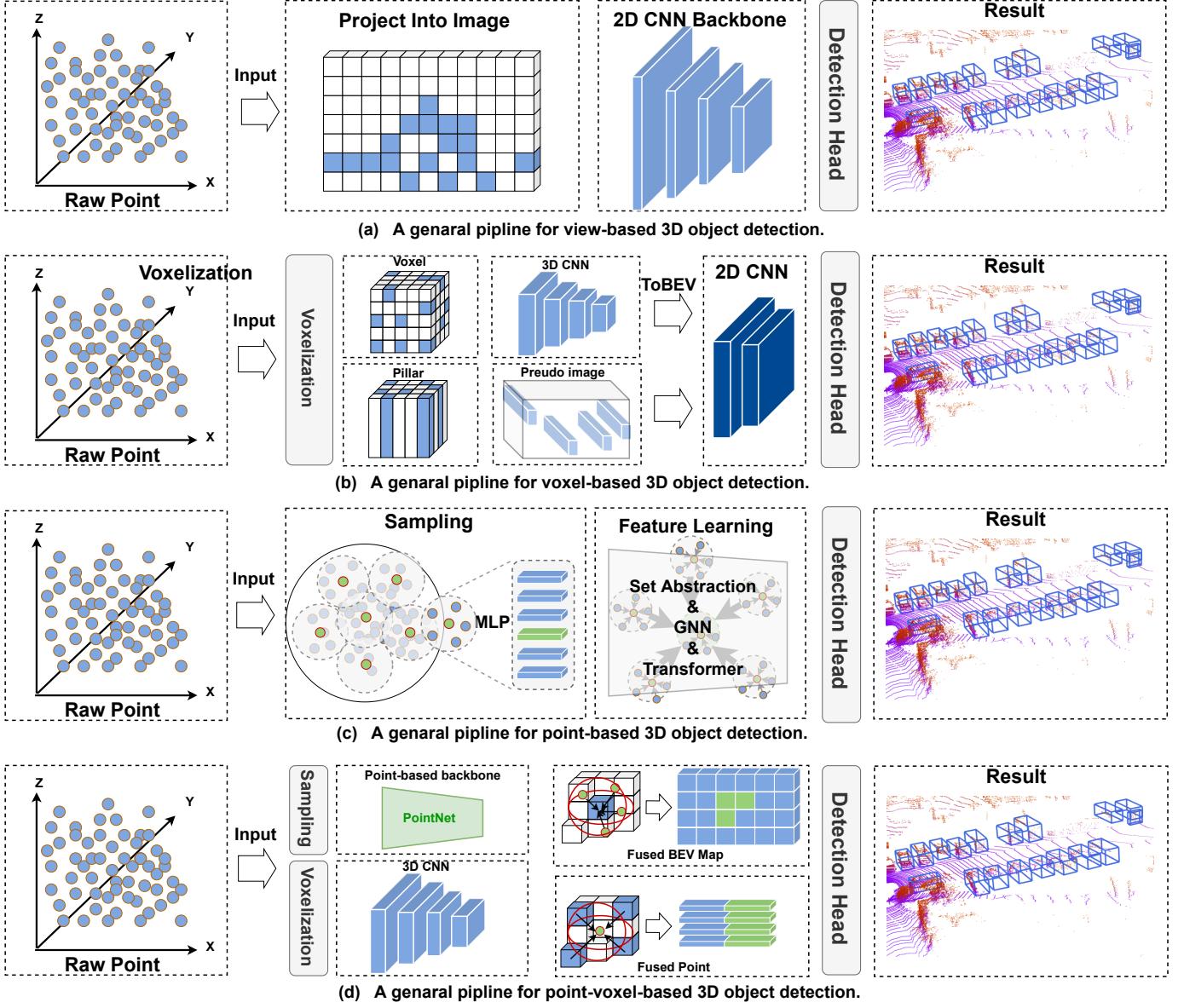


Fig. 8: The general pipelines for LiDAR-based 3D object detection.

each cell. PIXOR [403], which outputs oriented 3D object estimates decoded from pixel-wise neural network predictions, is a pioneering work in this field and followed by [175], [176], [404], [405]. These methods usually entailing three stages. First, point cloud is projected into a novel cell encoding for bird’s eye view projection. Later, both object location on the plane and its heading are estimated through a convolutional neural network originally designed for image processing. Considering scale variation and occlusion, RangeRCNN [173] and RangeIOUDet [175] introduced point view serves as a bridge from RV to BEV which provides pointwise features for models.

B. Voxel-based 3D object detection

Voxel-based methods propose to divide the sparse point cloud and assign the distributed point cloud into regular voxels,

forming the dense data representation, termed voxelization. Generally, the overall process of voxel-based methods is illustrated in Fig. 8. Compared to view-based methods, voxel-based methods leverage spatial convolution to effectively perceive 3D spatial information and achieve higher detection accuracy. Voxel-based methods face the following challenges:

- **High computational complexity:** Compared with camera-based methods, voxel-based methods require significant memory and computation resources due to the large number of voxels used to represent the 3D space.
- **Spatial information loss:** Due to the discrete nature of voxels, details and shape information can be lost or blurred during the voxelization process. Additionally, the limited resolution of voxels makes it challenging to accurately detect small objects.
- **Inconsistency in scale and density:** Voxel-based methods are typically performed on voxel grids with specific

scales and densities. However, due to the significant variations in object scales and point cloud densities across different scenes, making methods to adapt different scenes becomes challenging.

To overcome the aforementioned challenges, it is necessary to address the limitations of data representation, improve the network's feature capacity and target localization accuracy, and enhance the algorithm's understanding of complex scenes. Indeed, it is crucial for ensuring safety perception in autonomous driving. Although the optimization strategies of these methods may vary, they share common perspectives of model optimization: 1) data representation. 2) model structure.

1) Data representation: Voxel-based methods first rasterize point clouds into discrete grid representations. Grid representations are closely related to accuracy, computational complexity, and memory requirements. Using too large voxel size results in significant information impairment while using too small voxel size increases the burdens of computation and memory. As shown in Fig. 9, according to the height of the z -axis, the type of grid representations can be categorized into voxel and pillar.

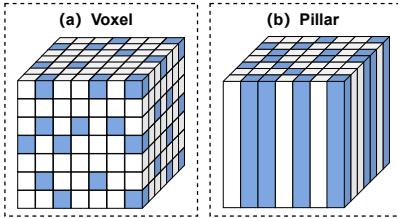


Fig. 9: Comparison of voxel voxelizeation with pillar voxelizeation. The blue cubes in the image represent a non-empty voxels.

a) Voxel: Voxel grid process divides the 3D space into regular voxel grids with size $(d_L \times d_W \times d_H)$ in the x, y, and z directions, respectively. Only non-empty voxel units that contain points are stored and used for feature extraction. However, due to the sparse distribution of point clouds, the majority of voxel units are empty. As a pioneering work in voxel-based methods [101]–[105], [108], [109], [112]–[115], [121], [122], [125], [129]–[131], [136], [143], [151], [182], [230], [251], VoxelNet [108] proposes a novel voxel feature encoding (VFE) layer to extract features from the points inside a voxel cell. Theb, following works [103], [104], [113], [114], [125], [149], [161] have extended the VoxelNet network by adopting similar voxel encoding approaches. Existing methods often perform local partitioning and feature extraction uniformly across all positions in the point cloud. This approach leads to limitations in the receptive field for distant regions and information truncation. Therefore, some works have proposed different approaches to voxel partitioning: 1) **Different coordinate systems.** Some approaches have reexamined voxel partitioning from different coordinate system perspectives, e.g. [153], [200] from cylindrical and [132] from spherical coordinate systems. Sphereformer [132] facilitates the aggregation of information from sparsely distant points by dividing the 3D space into multiple non-overlapping radial

windows using spherical coordinates (r, θ, ϕ) , thereby enhancing information integration from dense point regions. 2)

Multi-scale voxels. Some works generate voxels of different scales [115], [150] or use reconfigurable voxels [155], e.g. HVNet [150] proposes a hybrid voxel network which integrates different scales in the point-level voxel feature encoder (VFE). In addition, there are two series of approaches trying to incorporate additional information for voxel fusion. 1) **Additional temporal information.** Some methods [122], [126], [406]–[410] integrate point cloud data from multiple time steps to obtain global environmental information, effectively mitigating the effects of objects blocking each other, and providing a denser representation that captures more detailed spatial information. 2) **Additional spatial prior information.** Some works encode density information [120], [411]–[413] or voxel centroid information [120] in point cloud processing.

b) Pillar: Pillars can be considered as a special form of voxels. Specifically, point clouds are discretized into a grid uniformly distributed on the x-y plane, creating a set of pillars without binning along the z-axis. Pillar features can be aggregated from points through a PointNet [414] and then scattered back to construct a 2D BEV image for feature extraction. As the pioneering work in this series [118], [119], [123], [135], [156], [181], [183], PointPillar [118] firstly introduces pillar representation. Followed works have extended the ideas from 2D detection to PointPillars. PillarNet [183] adopts the ‘encoder-neck-head’ detection architecture to enhance the performance of pillar-based methods. SWFormer [135] and ESS [123] draw inspiration from the swin transformer [352] and apply a hierarchical window mechanism to pseudo-images, enabling the network to maintain a global receptive field while achieving faster inference speed. PillarNext [119] integrates a series of mature 2D detection techniques and achieves performance comparable to voxel-based methods.

2) Model Structure: Most voxel-based detectors consist of two fundamental components: voxel-based data representation and voxel-based neural networks. Specifically, there are primarily three major types of neural networks of voxel-based methods: 1) 2D CNNs used for processing BEV feature maps and pillars. 2) 3D CNNs for processing voxels. 3) Transformers for handling both voxels and pillars.

a) 2D CNN: 2D CNN is primarily used to detect 3D objects from a bird’s-eye view perspective, including processing BEV (Bird’s Eye View) feature maps and pillars [118], [119], [135], [181], [183]. Specifically, the 2D CNN used for processing BEV feature maps often come from well-developed 2D object detection networks, such as Darknet [415], ResNet [416], FPN [402], and RPN [401]. Some early voxel-based works drew inspiration from mature ideas in 2D detection, e.g. Voxel-FPN [115]. One significant advantage of 2D CNN compared to 3D CNN is its faster speed. However, due to its difficulty in capturing spatial relationships and shape information, 2D CNN typically exhibits lower accuracy.

b) 3D Sparse CNN: 3D Sparse CNN consists of two core operators: sparse convolution and submanifold convolution [417], which ensure that the convolutional operation is performed only on non-empty voxels. SECOND [109] imple-

ments efficient computation of sparse convolution [417] and submanifold convolution [418] operators to gain fast inference speed by constructing a hash table. Due to its outstanding performance, it's followed by [104], [112], [113], [125], [250]. However, the limited receptive field of 3D Sparse CNNs, leading to information truncation, restricts the model's feature extraction capabilities. Meanwhile, the sparse representation of features makes it challenging for the model to capture fine-grained object boundaries and detailed information. To optimize these issues, main optimization strategies have emerged: 1) Expanding the model's receptive field. Some methods [129], [130] extend the concept of large kernel convolution from 2D to 3D space or introduce additional downsampling layers in the model [112]. 2) Combining sparse and dense representations. Methods in this category typically utilize dense prediction heads to prevent information loss [108], [109], [113], [125], [372] or retrieve lost 3D information from the detection process [102], [113], [125], [168], [180], [372], or they add additional auxiliary tasks to the model [103], [104], [151], [201], [372], [419]. Methods employing dense prediction heads typically require high-resolution Bird's Eye View (BEV) feature maps for conducting dense predictions on them. Considering computational complexity, some recent methods aim to establish global sparse and local dense prediction relationships [124], [131]. Meanwhile, certain detection methods focus on recovering 3D information from the detection process, for instance, the pioneering two-stage detection work Voxel-RCNN [113], which aggregates early features around voxels near instances using the Voxel ROI Pooling module to recover lost 3D information. Subsequent works have designed approaches based on the Voxel-RCNN paradigm, such as using corner point [102], [104], [180] or keypoints from [105], [125].

Numerous methods resort to auxiliary tasks to enhance the spatial features and provide implicit guidance for accurate 3D object detection, including IOU prediction to rectify the object confidence scores [103], [104], [151], object shape completion to complete object shapes from sparse point clouds [162], [420], and object part estimation to gain 3D structure information by identifying the part information inside objects [201], [372].

c) Transformer: : In recent years, transformer [352], [353] has developed rapidly in Computer Vision and has shown amazing performance on numerous tasks. Therefore, many endeavors have been made to adapt Transformers to 3D object detection. Particularly, recent studies [253], [254] have confirmed the excellent robustness of transformer-based models, which will further advance research in the domain of safety perception for autonomous driving.

Compared with CNN, the query-key-value design and the self-attention mechanism make transformer modeling global relationships, resulting in a larger receptive field. However, the primary limitation for efficient application of Transformer-based models is the quadratic time and space complexity of the global attention mechanism. Hence, it's critical to design specialized attention mechanisms for Transformer-based 3D object detectors. Transformer [351], DETR [355], and ViT [353] are the works that have most significantly influenced 3D transformer-based methods [123], [126]–[128],

[135], [181], [223], [230]. They have each inspired subsequent 3D detection works in various aspects: the design of attention mechanisms, the architecture of encoders and decoders, and the development of patch-based inputs and architectures similar to visual transformers.

Inspired by transformer [351], VoTr [127] is the first work to incorporate transformer into a voxel-based backbone network, which is composed of sparse attention and sparse submanifold attention modules. Subsequent work [128] have continued to build on the foundation of voxel-transformer, further optimizing the temporal complexity of the attention mechanism. DETR [355] has inspired a range of networks to adopt an encoder-decoder structure akin to DETR's. Trans-Fusion [230] as a notable work, generates object queries from initial detections, applying cross-attention to LiDAR and image features within the Transformer decoder for 3D object detection. Meanwhile, many papers [123], [135], [181] try to explore and refine patch-based inputs mechanism from ViT [353] and the window attention mechanism from Swin Transformer [352], e.g. SST [123] and SWFormer [135] group local regions of voxels into patches, apply sparse regional attention, and then apply region shift to change the grouping. It is noteworthy that SEFormer [181] is the first to introduce object structure encoding into the transformer module.

C. Point-based 3D object detection

Benefiting from the prosperity of point cloud in deep learning [414], [421]–[423], the Point-based 3D object detection inherits many framework and proposes to directly detect object from the raw points without preprocessing. Compared to voxel-based methods, the raw points maximally retains the original information, which is beneficial for fine-grained feature acquisition. Meanwhile, a series of point-based backbone works [414], [421] naturally provide a strong baseline for point-based methods. However, as of now, the performance of point-based methods is still influenced by two factors: the number of contextual points and the context radius used in feature learning, e.g. increasing the number of contextual points can provide fine-grain 3D information but significantly increases the model's inference time. Similarly, reducing the context radius can achieve the same effect. Therefore, selecting appropriate values for these two factors enables the model achieve a balance between accuracy and speed. Specifically, to address the aforementioned issues, existing methods mostly focus on optimizing the two basic components of point-based 3D object detectors: 1) Point Cloud Sampling. 2) Feature Learning.

1) Point Cloud Sampling: FPS (Farthest Point Sampling), originating from the work on PointNet++ [421], is a point cloud sampling method extensively utilized in point-based methods. It aims to select a set of representative points from the raw points, such that their mutual distances are maximized, thereby optimally covering the entire spatial distribution of the point cloud.

PointRCNN [111], a pioneering two-stage detector in point-based methods, utilize the PointNet++ [421] with multi-scale grouping as backbone network. In stage-1, it generates 3D

proposals from point clouds in a bottom-up manner. The stage-2 network refines the proposals by combining semantic features and local spatial features. A similar framework proposed by [144]. Their model eliminates part of the background information with 2D image semantic segmentation.

However, existing methods relying on Farthest Point Sampling (FPS) still face several issues: 1) points irrelevant to detection also participate in the sampling process, leading to additional computational burden. 2) The distribution of points across different parts of an object is uneven, resulting in suboptimal sampling strategies. In subsequent works, design paradigms similar to FPS have been employed, with addressing the aforementioned issues, such as segmentation-guided background point filtering [144], [186], random sampling [424], feature space sampling [105], voxel-based sampling [107], [110], coordinate refinement [138] and ray-based grouping sampling [192].

2) Model Structure: The feature learning stage in point-based methods aims to extract discriminative feature representations from raw points. The neural network used in the feature learning phase should possess the following characteristics: 1) Invariance, where the point cloud backbone network should be insensitive to the ordering of input point clouds, 2) Local awareness, enabling the backbone network to perceive and model local regions and extract local features, 3) The ability to integrate contextual information, allowing the backbone network to extract features from both global and local contextual information.

Based on the aforementioned characteristics, a multitude of detectors have been designed for processing raw points. However, most methods can be categorized according to the core operators they utilize: 1) PointNet-based methods [111], [186], [195], [251], [425]. 2) Graph Neural Network-based methods [110], [134], [424], [426], [427]. 3) Transformer-based methods [138], [428].

a) PointNet-based: PointNet-based methods [111], [186], [195], [251], [425] primarily rely on the Set Abstraction [414] to perform downsampling on raw points, aggregation of local information, and integration of contextual information, while preserving the symmetry invariance of raw points. Point-RCNN [111], as the first two-stage work in point-based methods, achieved amazing performance at its time, yet it still faces the issue of high computational cost. Subsequent work [144], [186] has addressed this issue by introducing an additional semantic segmentation task during the detection process to filter out background points that contribute minimally to detection. Furthermore, some methods efforts have focused on resolving the issue of the uncontrolled receptive field in PointNet&PointNet++, such as through the use of GNN [161] or Transformer [138].

b) Graph-based: GNNs (Graph Neural Networks) possess key elements such as an adaptive structure, dynamic neighborhood, the capability to construct both local and global contextual relationships, and robustness against irregular sampling. These characteristics naturally endow GNNs with an advantage in handling irregular point clouds. Point-GNN [110], a pioneering work, designs a one-stage graph neural network to predict object with an auto-registration mechanism, merging

and scoring operation, which demonstrate the potential of using the graph neural network as a new approach for 3D object detection. Most graph-based point-based methods [110], [424], [426], [427], [429] aim to fully utilize contextual information. This motivation leaves room for further improvements in subsequent works [427], [429].

c) Transformer-based: Up to this point, a series of methods [126], [138], [217], [428], [430], [431] have explored the use of transformers for feature learning in point clouds and have achieved excellent results. Pointformer [138] introduced local and global attention modules for processing 3D point clouds. The local transformer module models interactions among points within local areas, aiming to learn contextually relevant regional features at the object level. The global transformer, on the other hand, focuses on learning context-aware representations at the scene level. Subsequently, the local-global Transformer combines local features with high-resolution global features to further capture dependencies between multi-scale representations. Group-free [428] directly utilize all points in the point cloud to compute features for each object candidate, where the contribution of each point is determined by an automatically learned attention module. Specifically, the authors adapted the Transformer to suit 3D object detection, enabling it to model both object-to-object and object-to-pixel relationships and extract object features without manual grouping. Moreover, by iteratively refining the spatial encoding of objects at different stages, the detection performance is further enhanced.

Point-based transformer directly process unstructured and unordered raw point clouds. This results in significantly higher computational complexity compared to structured voxel data. Consequently, the application of transformer-based methods in point-based methods is far less prevalent than in voxel-based methods.

D. Point-Voxel based 3D object detection

Point-based methods offer high resolution and preserve the spatial structure of the original data, but they suffer from high computational complexity and inefficiency in handling sparse data. In contrast, voxel-based methods provide a structured data representation, enhancing computational efficiency and facilitating the application of conventional convolutional neural network techniques. However, due to the discretization process, they often lose fine spatial details. Driven by these issues, PV-based methods were developed. Point-voxel methods aim to leverage the fine-grained information capture capabilities of point-based methods and the computational efficiency of voxel-based methods. By integrating these methods, point-voxel based methods enable a more detailed processing of point cloud data, capturing both the global structure and micro-geometric details. This is critically important for safety perception in autonomous driving, as the accuracy of decisions made by autonomous driving systems depends on high-precision detection results.

The key goal of point-voxel methods is to enable feature interplay between voxels and points via point-to-voxel or voxel-to-point transformations. The idea that leverages point-voxel feature fusion in backbones has been explored by

many works [116], [117], [120], [139], [146], [164]–[166], [168], [199], [371], [432], [433]. These methods fall into two categories: 1) ***Early Fusion***. The early fusion methods fuses [116], [146], [164]–[166], [199] voxel features and point features within the backbone network. 2) ***Late Fusion***. while the late fusion methods [117], [120], [139], [168], [371], [432], [433], typically a two-stage detection approach, uses voxel-based methods for initial proposal box generation, followed by sampling and refining key point features from the point cloud to enhance 3D proposals.

a) ***Early Fusion***: Some methods [116], [146], [163]–[166], [199] have explored using new convolutional operators to fuse voxel and point features, with PVCNN [116] potentially being the first work in this direction. In this approach, the voxel-based branch initially converts points into a low-resolution voxel grid and aggregates neighboring voxel features through convolution. Then, through a process called devoxelization, voxel-level features are transformed back to point-level features and fused with features obtained from the point-based branch. The point-based branch extracts features for each individual point. Since it does not aggregate neighboring information, the method can operate at a higher speed. Following closely, SPVCNN [199] which builds upon PVCNN, extends PVCNN to the domain of object detection. Other methods attempt to make improvements in different perspectives, such as auxiliary tasks [146], [163] or multiscale feature fusion [164]–[166].

b) ***Late Fusion***: The methods in this series predominantly adopt a two-stage detection framework. Initially, voxel-based methods are employed to generate preliminary object proposals. This is followed by a refinement phase, where point-level features are leveraged for the precise delineation of detection boxes. Shi *et al.* proposed PV-RCNN [371], a milestone in PV-based methods. It utilizes SECOND [109] as the first-stage detector and proposes a second-stage refinement stage with a ROI grid pool for the fusion of keypoint features. Later works in this domain predominantly follow the aforementioned paradigm, focusing on advancements in second-stage detection. Notable developments include, attention mechanisms [139], [167], [168], scale-aware pooling [433] and point density-aware refinement modules [120].

PV-based methods simultaneously possess the computational efficiency of voxel-based approaches and the capability of point-based methods to capture fine-grained information. However, the construction of point-to-voxel or voxel-to-point relationships, along with the feature fusion of voxels and points, incurs additional computational overhead. Consequently, compared to voxel-based methods, PV-based methods can achieve better detection accuracy, but at the cost of increased inference time.

E. Analysis: Accuracy, Latency, Robustness

In the autonomous driving sector, the development of LiDAR-based 3D object detection solutions is advancing rapidly. A series of works [1], [2], [242], [252], [269]–[275], [344]–[350] have comprehensively summarized the current technological roadmaps, such as the extensive review

of LiDAR-based solutions by the Shanghai AI Lab and SenseTime Research [269]. However, there remains a lack of summarization and guidance from the perspective of safety perception and cost impact in autonomous driving. Therefore, in this section, following an analysis of the technological roadmaps and current state of LiDAR-based solutions, we intend to base our discussion on the fundamental principles of ‘Accuracy, Latency, and Robustness.’ This is aimed at providing guidance for the practical implementation of economically efficient and safe sensing in autonomous driving.

1) ***Accuracy***: Referencing Section III discussion on camera-based methods, to investigate the core factors influencing the performance of LiDAR-based methods similarly, we selected representative and cutting-edge methods from each category for a comparative performance analysis, as shown in Fig 10. The current scenario indicates that the performance of view-based methods is significantly lower than the other three categories. view-based approaches aim to transform point clouds into pseudo-images, then process data using 2D detectors. Although this is favorable for inference speed, it comes at the cost of sacrificing some 3D spatial information. As discussed in the section III, camera-based detection methods that can effectively recover 3D space often exhibit superior detection performance. For example, the detection performance of binocular methods surpasses that of monocular methods, and methods based on the BEV paradigm outperform others. Therefore, the effective representation of 3D spatial information is a primary factor impacting the performance of LiDAR-based methods.

In the development of LiDAR-based detection methods, initially, point-based and PV-based approaches outperformed voxel-based methods. However, over time, methods represented by Voxel RCNN [113], utilizing ROI pool modules capable of effectively aggregating fine-grained information, have brought comparable or superior performance to voxel-based approaches. The distinction of the Voxel-RCNN approach from earlier voxel-based methods lies in its ROI pooling module, which effectively aggregates local fine-grained information, addressing the issue of loss of detailed 3D spatial information in the voxelization process. As shown in Fig. 6(c) and (d), the comparison between single-stage [109], [118] and two-stage [113], [127] LiDAR methods indicates that the latter’s use of fine-grained data significantly enhances accuracy. This factor also contributed to the early advantage of point-based and PV-based methods over voxel-based approaches. However, recent voxel-based methods, focusing on extracting and utilizing detailed point cloud information, have narrowed this gap in precision. This phenomenon underscores the importance of fine-grained point cloud information in improving detection accuracy.

Additionally, it is important to note the accuracy differences between transformer-based methods and those based on CNNs or PointNet, as shown in Fig. 10. Due to both global and local self-attention mechanisms that capture contextual information from a large spatial range, transformers have an advantage in modeling long-range dependencies. The receptive field of 3D sparse CNNs is constrained by the size of the convolutional kernel and the spatial discontinuities of sparse features, leading

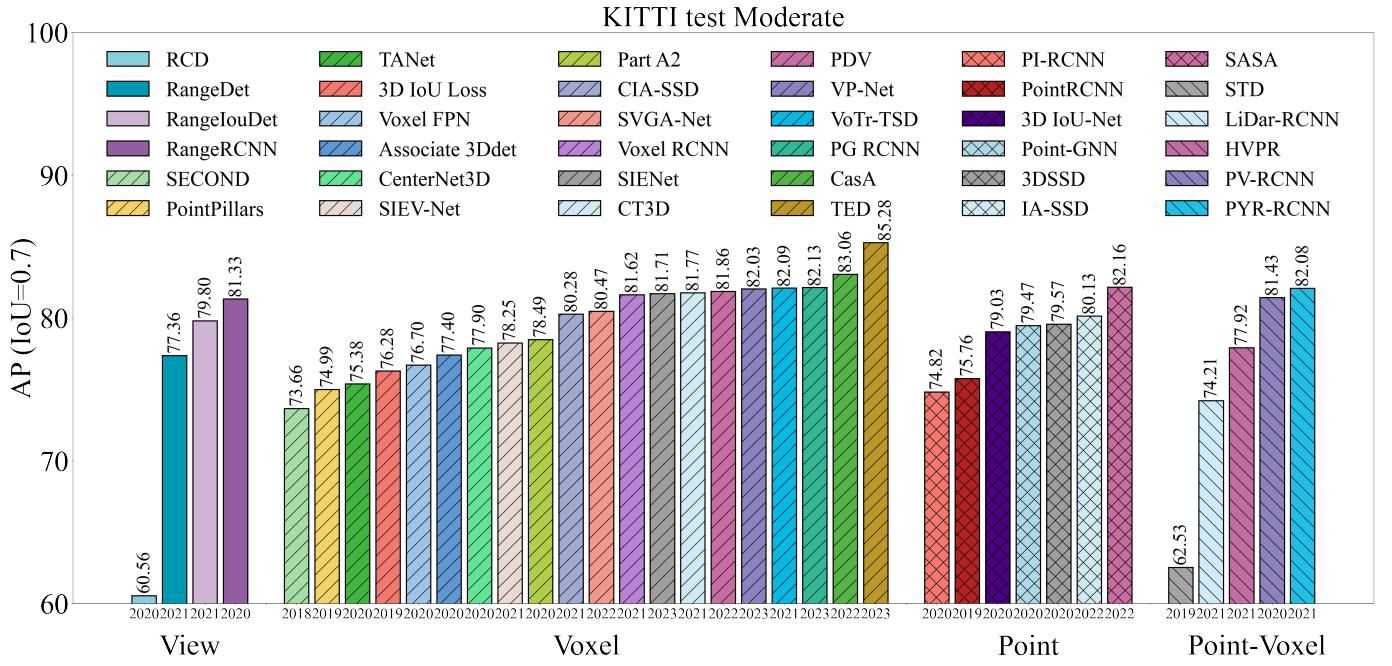


Fig. 10: AP_{3D} comparison of View based [173]–[176], Voxel based [101], [102], [109], [113], [115], [118], [120], [121], [127], [134], [139], [145], [147], [151], [182], [372]–[374], [434], [435], Point based [105], [110], [111], [186], [369], [370], [436], and Point-Voxel based [165], [168], [251], [371], [433] on KITTI moderate dataset.

to information truncation issues and thus inferior performance compared to transformers. Recent related works [129], [130] provide a good demonstration that when the receptive field of 3D convolutions is expanded, methods based on 3D sparse convolutions can achieve the performance of transformer-based methods. Therefore, effective global relationship modeling and avoiding information truncation are other key factors in enhancing the accuracy of LiDAR-based detection.

2) **Latency:** The section III highlights latency's importance in autonomous driving safety and user experience. While camera-based methods tend to outperform LiDAR-based methods in terms of inference speed, the latter still maintain a competitive edge due to their accurate 3D perception. We conducted tests using an A100 graphics card to measure the FPS of significant LiDAR-based approaches, and evaluated their performance using the original research's AP and NDS metrics. As shown in Fig. 6, it indicates that view-based methods excel in model latency due to the reduction in point cloud dimensions and the efficiency of 2D CNNs. Voxel-based methods achieve exceptional inference speed due to the use of structured voxel data and well-optimized 3D sparse convolutions. However, point-based methods face challenges in applying efficient operators during data preprocessing and feature extraction stages due to the irregular representation of point clouds. Point-GNN [110] is an extreme example of this, with model latency nearly ten times that of contemporary voxel algorithms.

To conclude, optimizations improving detection performance typically compromise inference speed in autonomous driving models. Achieving a balance between accuracy and speed is an evolving challenge in this field. Future studies should prioritize the simultaneous improvement of accuracy,

FPS and latency reduction in order to meet the urgent requirements of real-time response and safety in autonomous driving.

3) **Robustness:** Previous comprehensive reviews have not focused significantly on the topic of robustness. Presently, research works [253], [254], [287], [288], [388]–[390] like RoboBEV [253], Robo3D [288] on 3D object detection incorporate considerations of robustness, exemplified by factors such as sensor misses. Robo-LiDAR [286] represents the first comprehensive exploration solely dedicated to the robustness of LiDAR-based methods. In a manner akin to BR3D [254], this method evaluates robustness by integrating disturbances into datasets pertinent to 3D object detection, such as KITTI [255]. The method involves proposing a variety of noise types and 25 typical degradations associated with object and scene-level natural weather conditions, noise interferences, density variations, and object transformations. In this section, we will combine the work of Ref. [254] and Robo-LiDAR [286] with the aim of systematically analyzing the robustness of LiDAR-based methods. As shown in the Table IV, generally, LiDAR-based methods exhibit higher robustness to noise compared to camera-based methods. It is important to note the performance differences between LiDAR-based methods and multimodal methods in noisy environments. In multimodal methods [221], [227], [228], [230], [232], [237], [247], the complementary interplay of data types becomes evident when disturbances are limited to LiDAR sensor data. In such scenarios, image data can partially mitigate the impact on point cloud integrity, consequently elevating the performance of fusion methods above that of methods relying solely on LiDAR. When disturbances affect both image and point cloud data concurrently, the efficacy of

TABLE VI: Comparison with LiDAR-based detectors on corrupted validation sets of **KITTI** from Ref. [286] on **Car** detection with $CE_{AP}(\%)$. $CE_{AP}(\%)$ denotes **Corruption Error** from Ref. [286]. The best one is highlighted in **bold**.

Corruption			Point-voxel		Point		Voxel					Average
			PVRCNN-voxel	PointRCNN	SECOND	BtcDet	VoTr-SSD	VoTr-TSD	SE-SSD	CenterPoint		
Scene-level	Weather	rain	25.11	23.31	21.81	31.07	28.17	26.77	29.51	25.83	26.45	
		snow	44.23	37.74	34.84	54.07	54.10	52.18	49.19	38.74	45.64	
		fog	1.59	3.52	1.60	1.81	1.77	2.02	1.59	1.11	1.88	
	Noise	uniform_rad	10.19	8.32	9.51	9.13	3.79	4.11	9.34	8.15	7.82	
		gaussian_rad	13.02	9.98	12.13	10.83	4.84	5.18	11.02	10.17	9.65	
		impulse_rad	2.20	3.86	2.23	2.50	2.25	3.57	1.18	1.8	2.46	
		background_upsample	2.93	6.49	2.41	1.82	4.59	3.6	2.14	1.86	2.46	
			0.81	1.84	0.31	0.95	0.37	0.71	0.55	0.46	0.75	
	Density	cutout	3.75	3.97	4.27	3.99	4.51	3.59	4.26	4.11	4.0	
		local_dec	14.04	-	13.88	14.55	14.44	12.50	17.01	14.64	14.44	
		local_inc	1.40	3.34	1.33	2.20	1.66	1.69	0.90	0.95	1.68	
		beam_del	0.58	0.79	0.73	0.88	0.80	0.53	1.07	0.47	0.73	
		layer_del	2.94	3.46	3.10	3.39	3.29	3.16	3.37	2.67	3.17	
Object-level	Noise	uniform	15.44	12.95	9.48	12.6	2.76	4.81	6.99	6.51	8.94	
		gaussian	20.48	17.62	12.98	17.05	4.72	7.46	9.56	9.49	12.42	
		impulse	3.3	4.7	2.53	4.07	2.88	4.29	2.2	2.11	3.26	
		upsample	1.12	1.95	0.67	1.33	0.08	0.4	0.22	0.16	0.74	
	Density	cutout	15.81	15.62	14.99	15.62	15.07	16.09	16.51	14.06	15.47	
		local_dec	14.38	14.16	13.23	14.26	12.66	14.41	15.08	12.52	13.84	
		local_inc	13.93	14.19	13.74	13.56	11.34	13.05	11.03	11.64	12.81	
	Transformation	shear	37.27	40.96	40.35	41.37	39.52	37.85	40.35	40.0	39.71	
		FFD	32.42	38.88	33.15	36.77	33.14	34.26	37.96	32.86	34.93	
		rotation	0.60	0.47	0.31	0.97	0.39	0.75	0.27	0.38	0.52	
		scale	5.78	8.13	6.96	5.81	8.53	6.50	6.53	7.50	6.97	
		translation	3.82	3.03	3.24	4.58	4.88	5.34	1.37	3.91	3.77	
mCE			11.49	11.64	10.39	12.21	10.42	10.60	11.17	10.09	11.01	

most multimodal methods significantly diminishes.

As shown in the Table VI, under various noise conditions, LiDAR-based methods experience varying degrees of accuracy decline, with the most significant reduction observed in extreme weather noise scenarios. These results indicate an urgent need in the field of autonomous driving to address the robustness issue of point cloud detectors. For most types of corruptions, voxel-based methods generally exhibit greater robustness than point-based methods. A plausible explanation is that voxelization, through the spatial quantization of a group of adjacent points, mitigates the local randomness and spatial information disruption caused by noise and density degradation. Specifically, for severe corruptions (e.g., shear, FFD in the Transformation), the point-voxel-based method [371] exhibits greater robustness. PointRCNN [111] does not show the highest robustness against any form of corruptions, highlighting potential limitations inherent in point-based methods.

Compared to single-stage detectors [109], [127], [143], two-stage detectors [111], [125], [127], [142], [371] exhibit poorer robustness to common degradations, as indicated by lower mCE_{AP} scores. One possible cause is that corrupted data could affect the proposal generation of stage 1, and the low-quality proposals significantly affect the BBox regression of stage 2. In summary, single-stage detectors demonstrate greater robustness against scene-level corruptions and object-level corruptions and density disruptions, while two-stage detectors are mainly more robust against weather and scene-level density degradations. As for Transformation corruptions, one-stage detectors present better robustness on FFD, rotation, translation and two-stage detectors work better under corruptions of shear, scale.

TABLE VII: $CE_{AP}(\%)$ of LiDAR-based detectors with different proposal architectures on corrupted validation sets of **KITTI** from Ref. [286] on **Car** detection. $CE_{AP}(\%)$ denotes **Corruption Error** from Ref. [286]. The best one is highlighted in **red** (One-stage [109], [143]) or **blue** (Two-stage [110], [125], [127], [371]).

Corruption			One-stage	Two-Stage
Sence-level	Weather	rain	26.50	26.42
		snow	46.04	45.39
		fog	2.01	-
	Noise	uniform_rad	7.55	7.98
		gaussian	9.33	9.84
		impulse_rad	1.30	1.02
		background	3.05	3.38
		upsample	0.41	0.95
	Density	cutout	4.35	3.88
		local_dec	15.12	13.93
		local_inc	1.30	1.92
		beam_del	0.87	0.65
		layer_del	3.25	3.12
Object-level	Noise	uniform	6.41	10.46
		gaussian	9.09	14.42
		impulse	2.54	3.69
	Density	upsample	0.32	0.99
		cutout	15.52	15.44
		local_dec	13.66	13.95
		local_inc	12.04	13.27
	Transformation	shear	40.07	39.49
		FFD	34.75	35.04
		rotation	0.32	0.63
		scale	7.34	6.74
		translation	3.16	4.14
mCE			10.66	11.21

V. MULTIMODAL 3D OBJECT DETECTION

multimodal 3D object detection refers to the technique of using data features from different sensors and integrating these features to achieve complementarity, thus enabling the detection of 3D objects. As shown in Fig. 11, they particularly emphasizes the combination of image data and point cloud data. Image data is rich in semantic features, such as color and texture, but often lacks depth information. In contrast, point cloud data provides depth information and geometric structure, which is crucial for accurately perceiving and interpreting the 3D characteristics of a scene. Since a single type of sensor cannot fully and accurately perceive the 3D environment, multimodal 3D object detection acquires features with rich semantic information by fusing various types of data.

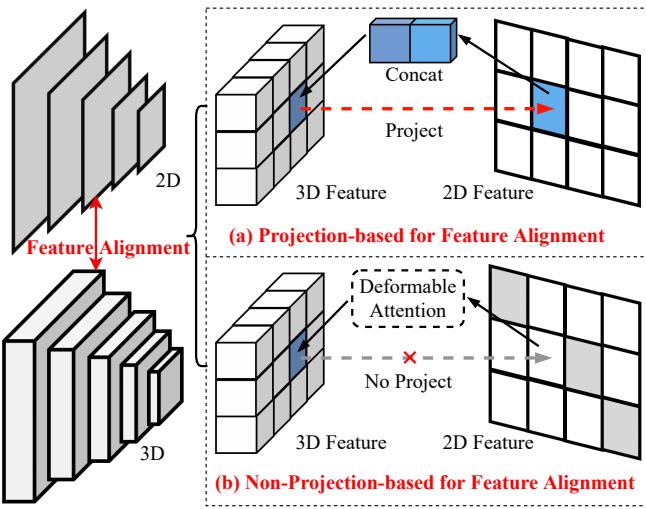


Fig. 11: Projection for feature fusion vs. Non-Projection for feature fusion.

In the field of autonomous driving, there are a variety of fusion methods for multimodal 3D object detection. Previous reviews [1], [2], [242], [252], [269]–[275], [344]–[350] have mostly classified these methods based on different stages of fusion (early, middle, late), but this classification is overly simplistic and does not fully consider the special requirements of autonomous driving. Given the fundamental differences between the two heterogeneous modalities of point clouds and images, the alignment step in multimodal fusion is particularly critical. It ensures the consistency and accuracy of information from different sensors and data sources during the fusion process. In autonomous driving, the key to achieving feature alignment lies in whether to use a calibration matrix (also known as a projection matrix). However, the inherent error of the calibration matrix, being a type of prior knowledge, poses a challenge. Some works like [236], [437] avoid using the projection matrix and reduce projection errors by adopting learning methods.

Therefore, based on different methods of feature alignment, we can categorize multimodal 3D object detection methods into: (1) projection-based for feature alignment, (2) model-based for feature alignment. This taxonomy is more detailed and scientific, better reflecting the characteristics and progress

of multimodal 3D object detection methods in the field of autonomous driving.

A. Projection-based 3D object detection

Projection-based 3D object detection refers to the use of projection matrix during the feature fusion stage to achieve the integration of point cloud and image features. It is important to clarify that the focus here is on projection during the feature fusion period, rather than those in the fusion stage, which includes projections needed for processes such as data augmentation. As shown in Fig. We have developed a more detailed classification of Projection-based 3D object detection based on the different types of projection used in the fusion stage, including Point-Projection-based [222], [226], [227], [376], [383], [438]–[443], Feature-Projection-based [232], [250], [377], [444]–[449], Auto-Projection-based [106], [233], [234], [243], [247], [369], [378], [384], [450], [369] and Decision-Projection-based methods [107], [196], [380]–[382], [451]–[454].

1) Point-Projection-based 3D object detection: Point-Projection-based 3D object detection methods [222], [383], [438]–[443] involve a process of projecting image features onto raw point clouds to enhance the representational capability of the original point cloud data. The initial step in these methods is to establish a strong correlation between LiDAR points and image pixels, which is achieved using calibration matrices. Following this, the point cloud features are enhanced by augmenting them with additional data. This augmentation takes two forms: either through the incorporation of segmentation scores [222], [438], [456] or by using CNN features [226], [227], [376], [383], [443] from the correlated pixels. PointPainting [222] and PointAugmenting [383] represent advancements in multi-model 3D object detection methods by enhancing the traditional cut-and-paste augmentation. These techniques aim to seamlessly integrate data from different domains, such as point clouds and 2D imagery, while carefully managing potential overlaps or collisions between objects in both domains. PointPainting enhances LiDAR points by appending segmentation scores. However, it has limitations in effectively capturing the color and texture details present in images. To address these shortcomings, more sophisticated approaches like FusionPainting [456] have been developed, following a similar paradigm. MVP [443] builds upon the concept of PointPainting [222]. It initially utilizes image instance segmentation and establishes an alignment between the segmentation masks and the point cloud using a projection matrix. The key distinction of MVP lies in its approach to sampling: it randomly selects pixels within each range, ensuring consistency with the points in the point cloud. These selected pixels are then linked to their nearest neighbors in the point cloud. The depth value of the LiDAR point in this linkage is assigned as the depth of the corresponding pixel. Subsequently, these points are projected back to the LiDAR coordinate system, resulting in the generation of virtual LiDAR points.

2) Feature-Projection-based 3D object detection: In contrast to Point-Projection-based methods, Feature-Projection-based 3D object detection methods [129], [232], [241], [246],

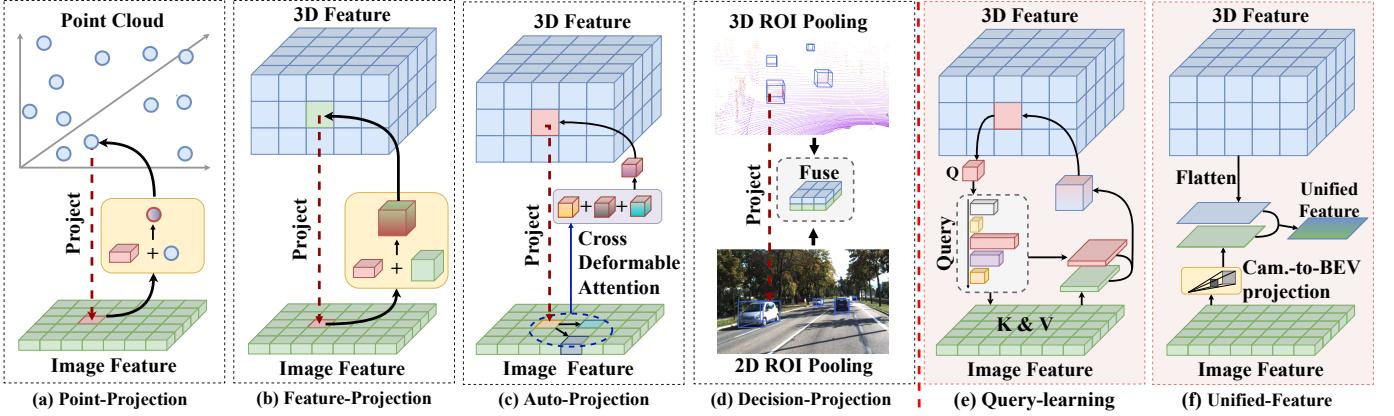


Fig. 12: Projection-based 3D object detection: (a), (b), (c), (d). Non-Projection-based 3D object detection: (e), (f). (a) Point-Projection-based methods [222], [226], [227], [376], [383], [438]–[443] integrates image features with the raw point cloud, entering the LiDAR-based pipeline. (b) Feature-Projection-based methods [232], [250], [377], [444]–[449] merges image features with point cloud features, entering the LiDAR-based pipeline. (c) Auto-Projection-based methods [106], [233], [234], [243], [247], [369], [378], [384], [450] employs solutions such as Cross Deformable Attention or Graph Match to enhance feature fusion through neighbor augmentation or offset learning on direct projection. (d) Decision-Projection-based methods [107], [196], [380]–[382], [451]–[454] performs projection and fuses ROI or detection results. (e) Query-Learning-based methods [230], [236], [237], [245], [437], [455] achieve feature fusion by querying image features with point cloud features through cross-attention, without the utilization of projection matrices. (f) Unified-Feature-based methods [136], [137], [221], [223], [225], [228], [231], [235], [240], [356], [375], [385]–[387] unify heterogeneous modalities into a common modality. Projection matrices are commonly employed during the modality unification process, while they are not required during fusion. They yield highly robust multimodal features and stands as the state-of-the-art solution for 3D object detection.

[250], [377], [445], [446], [449] primarily focus on fusing point cloud features with image features during the feature extraction phase of point clouds. During this fusion process, point cloud features are projected onto corresponding image features, and subsequently, these image and point cloud features are integrated together. This process is achieved by applying a calibration matrix to transform the voxel’s three-dimensional coordinate system into the pixel coordinate system of the image, thereby facilitating the effective fusion of point cloud and image modalities. Specifically, the projection of a three-dimensional point cloud onto the image plane can be articulated as follows:

$$z_c \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = h\mathcal{K} \begin{bmatrix} R & T \end{bmatrix} \begin{bmatrix} P_x \\ P_y \\ P_z \\ 1 \end{bmatrix}, \quad (6)$$

where, P_x , P_y , and P_z represent the three-dimensional spatial coordinates of the LiDAR points, while u and v denote the corresponding two-dimensional coordinates. The term z_c indicates the depth of the point’s projection on the image plane. Additionally, \mathcal{K} represents the intrinsic parameters of the camera, and R and T signify the rotation and translation of the LiDAR relative to the camera’s reference frame, respectively. The factor h accounts for the scale change due to downsampling.

A quintessential example of the Feature-Projection-based method, ContFuse [246], employs continuous convolution to amalgamate multi-scale convolutional feature maps from each sensor. Within this technique, the projection of the point cloud facilitates the correspondence between the image and

the Bird’s Eye View (BEV). In essence, Feature-Projection-based 3D object detection method is accomplished during the point cloud feature extraction phase. Compared to Point-Projection-based methods, they do not perform fusion on the original point cloud but achieve a profound depth feature fusion, resulting in more robust performance.



Fig. 13: Examples of misalignment between point clouds and images.

3) Auto-Projection-based 3D object detection: As shown in Fig. 13, a partial image from the KITTI [255] dataset exemplifies that projection inaccuracies persist even in this classic clean dataset. Consequently, the issue of projection errors cannot be completely eliminated by manual calibration, but rather, they can only be mitigated. This is a frequent challenge in practical dataset deployments. Many studies like Point & Feature-Projection-based methods have performed fusion through direct projection without addressing the projection error issue. A few works [106], [233], [234], [243], [247], [378], [384], [450] have sought to mitigate these errors through approaches such as projection offsets and neighboring

projections. For instance, Deformable Cross Attention [354] has been employed to learn offsets in the context of already projected data. We have systematically reviewed and synthesized methods that tackle projection errors, designating them as Auto-projection-based 3D object detection methods. As representative works addressing feature alignment, HMFI [243], GraphAlign [233], and GraphAlign++ [234] utilize the a priori knowledge of projection calibration matrices to project onto corresponding images for local graph modeling. This approach simulates the intermodal relationships, enabling multimodal 3D object detectors to effectively identify more appropriate alignment relationships, thereby achieving faster and more accurate feature alignment between modalities. AutoAlignV2 [384] focuses on sparse learnable sampling points for cross-modal relational modeling, enhancing calibration error tolerance and significantly accelerating feature aggregation across different modalities. In summary, Auto-Projection-based 3D object detection methods mitigate errors arising from feature alignment by leveraging neighbor relationships or neighbor offset, thereby enhancing robustness in multimodal 3D object detection.

4) Decision-Projection-based 3D object detection:

Decision-Projection-based 3D object detection methods [107], [196], [380]–[382], [451]–[454], as early implementations of multimodal 3D object detection schemes, use projection matrices to align features in Regions of Interest (RoI) or specific results. These methods are primarily focused on the alignment of features in localized areas of interest or specific detection outcomes. Graph-RCNN [107] project the graph node to the location in the camera image and collect the feature vector at that pixel in the camera image through bilinear interpolation. F-PointNet [381] performs detection of the 2D image to determine the class and localization of the object, and for each detected object, the corresponding Point clouds in 3D space is obtained through the conversion matrix of calibrated sensor parameters and 3D space. MV3D [453] employs a transformation of the LiDAR point cloud into Bird’s Eye View (BEV) and Front View (FV) projections for generating proposals. During this process, a specialized 3D proposal network is used to create precise 3D candidate boxes. These 3D proposals are then projected onto feature maps from multiple perspectives to facilitate feature alignment between the two modalities. Differing from MV3D [453], AVOD [452] streamlines this approach by omitting the FV component and introducing a more refined region proposal mechanism. In summary, Decision-Projection-based 3D object detection methods primarily achieve feature fusion at a high-level through projection, with limited interactivity between heterogeneous modalities. This often leads to the alignment and fusion of erroneous features, resulting in issues of reduced accuracy and robustness.

B. Non-Projection-based 3D object detection

Non-Projection-based 3D object detection methods achieve fusion without relying on feature alignment, thereby yielding robust feature representations. They circumvent the limitations of camera-to-LiDAR projection, which often reduces the se-

mantic density of camera features and impacts the effectiveness of techniques like Focals Conv [232] and PointPainting [222]. Non-Projection-based methods typically employ cross-attention mechanisms or the construction of a unified space to address the inherent misalignment issues in direct feature projection. These methods are primarily divided into two categories: (1) Query-Learning-based [230], [236], [237], [245], [437], [455] and (2) Unified-feature-based [136], [137], [221], [223], [225], [228], [231], [235], [356], [375], [385]–[387]. Query-Learning-based methods entirely negate the need for alignment during the fusion process. Conversely, Unified-feature-based methods, though constructing a unified feature space, do not completely avoid projection; it usually occurs within a single modality context. For example, BEVFusion [231] utilizes LSS [316] for camera-to-BEV projection. This process, taking place before fusion, demonstrates considerable robustness in scenarios with feature misalignment.

1) **Query-Learning-based 3D object detection:** Query-Learning-based 3D object detection methods, as exemplified by works such as [230], [236], [237], [245], [437], [455], eschew the necessity for projection within the feature fusion process. Instead, they attain feature alignment through cross-attention mechanisms before engaging in the fusion of features. Point cloud features are typically employed as queries, while image features serve as keys and values, facilitating a global feature query to acquire highly robust multimodal features. Furthermore, DeepInteraction [237] incorporates multimodality interaction, wherein point cloud and image features are utilized as distinct queries to enable further feature interaction. In comparison to the exclusive use of point cloud features as queries, the comprehensive incorporation of image features leads to the acquisition of more resilient multimodal features. Overall, Query-Learning-based 3D object detection methods employ a transformer-based structure for feature querying to achieve feature alignment. Ultimately, the multimodal features are integrated into LiDAR-based pipelines, such as Center-Point [125].

2) **Unified-Feature-based 3D object detection:** Unified-feature-based 3D object detection methods, represented by works such as [136], [137], [221], [223], [225], [228], [231], [235], [356], [375], [385]–[387], generally employ projection before feature fusion, achieving the pre-fusion unification of heterogeneous modalities. In the BEV fusion series, which utilizes LSS for depth estimation [223], [231], [385], [386], the front-view features are transformed into BEV features, followed by the fusion of BEV image and BEV point cloud features. Alternatively, CMT [225] and UniTR [356] employ transformers for tokenization of point clouds and images, constructing an implicit unified space through transformer encoding. CMT [225] utilizes projection in the position encoding process, but entirely avoids dependency on projection relations at the feature learning level. FocalFormer3D [375], FUTR3D [228], and UVTR [136] leverage transformers’ queries to implement schemes similar to DETR3D [88], constructing a unified sparse BEV feature space through queries, thus mitigating the instability introduced by direct projection. VirConv [221], MSMDFusion [387], and SFD [235] construct a unified space through pseudo-point clouds, with the projection occur-

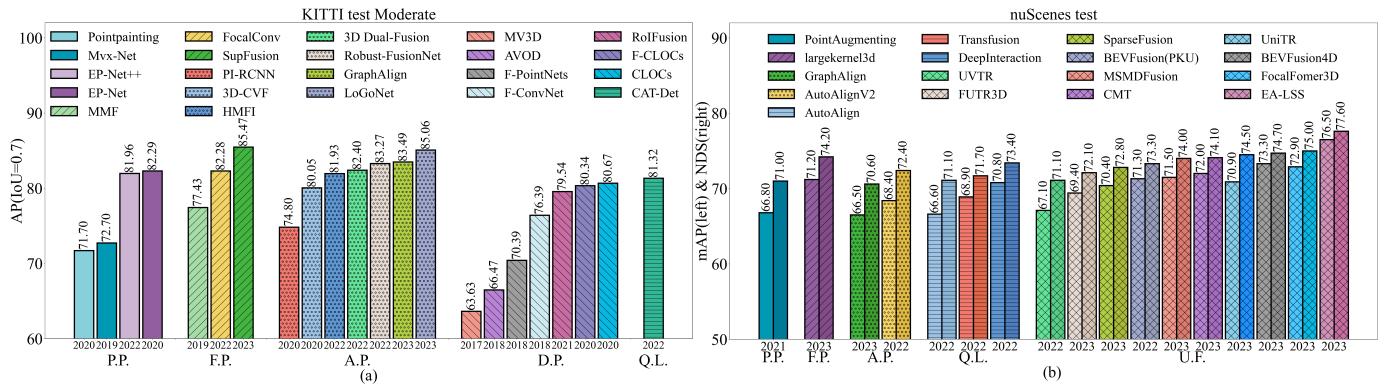


Fig. 14: Projection-based 3D object detection: P.P. (Point-Projection-based), F.P. (Feature-Projection-based), A.P. (Auto-Projection-based), D.P. (Decision-Projection-based), Non-Projection-based 3D object detection: Q.L.(Query-Learning-based), U.F. (Unified-Feature-based). (a) AP_{3D} comparison of Point-Projection-based [222], [226], [227], [376], Feature-Projection-based [232], [241], [377], Auto-Projection-based [106], [233], [243], [247], [369], [378], [450], Decision-Projection-based [196], [379], [380], [382], [452]–[454], and Query-Learning-based [245] on KITTI test moderate dataset. (b) The mAP (left) and NDS (right) comparison of Point-Projection-based [383], Feature-Projection-based [129], Auto-Projection-based [233], [384], Query-Learning-based [230], [237], [437], Unified-Feature-based [136], [223], [225], [228], [231], [356], [375], [385]–[387] and on the nuScenes test dataset.

ring before feature learning. The issues introduced by direct projection are addressed through subsequent feature learning. In summary, Unified-feature-based 3D object detection methods [136], [137], [221], [223], [225], [228], [231], [235], [356], [375], [385]–[387] currently represent high-precision and robust solutions. Although they incorporate projection matrices, such projection does not occur between multimodal fusion, distinguishing them as Non-Projection-based 3D object detection methods. Unlike Auto-Projection-based 3D object detection approaches, they do not directly address projection error issues but instead opt for unified space construction, considering multiple dimensions for multimodal 3D object detection, thereby obtaining highly robust multimodal features.

C. Analysis: Accuracy, Latency, Robustness

In the preceding Sections III-D, IV-E, we have conducted a comprehensive analysis of ‘Accuracy, Latency, Robustness’ for camera-only and LiDAR-only approaches. Subsequently, we extend our examination to multimodal 3D object detection methods, employing a similar analytical framework.

1) Accuracy: As shown in Fig.14, we conducted comparative evaluations on both the KITTI test and nuScenes test datasets. The majority of Projection-based 3D object detection methods have predominantly undergone experimentation on the KITTI dataset, with only a minority extending their evaluation to nuScenes. As shown in Fig.14 (a), it is evident that Feature-Projection-based and Auto-Projection-based methods exhibit superior overall performance, while Decision-Projection-based methods, primarily dated prior to 2020, tend to manifest relatively lower Average Precision (AP) metrics. A scant few Non-Projection-based 3D object detection methods, such as CAT-Det, have been experimented with on the KITTI dataset. As shown in Fig.14 (b), the latest methods predominantly belong to the Unified-Feature-based methods, underscoring the suitability of the panoramic camera

offered by nuScenes for achieving modality-unifying strategies like BEVFusion [231]. Overall, it is discernible that Non-Projection-based methods present more effective solutions in terms of Accuracy metrics (e.g., AP, mAP, NDS, etc.).

2) **Latency**: As shown in Fig. 6, we conducted a comparative analysis of mono-modal 3D object detection methods (LiDAR-only and Camera-only) and multimodal 3D object detection on the KITTI and nuScenes datasets, presenting scatter plots for Latency (FPS) and Accuracy metrics (AP, mAP, NDS, etc.). It is noteworthy that, in comparison to mono-modal 3D object detection methods (LiDAR-only and Camera-only), multimodal 3D object detection approaches generally exhibit lower FPS.

As shown in Fig. 6 (e), the results on the KITTI dataset indicate that GraphAlign excels in both AP and FPS metrics. Additionally, LoGoNet [247], Focals Conv [232], and EP-Net [226] demonstrate outstanding performance. Yes, the provided text contains a few errors. As shown in Fig. 6 (f), GraphAlign [233] maintains its position as having the highest FPS, but its NDS performance is suboptimal on the nuScenes dataset. In contrast, UniTR performs exceptionally well in both NDS and FPS metrics. Overall, it can be observed that within Projection-based methods, Auto-Projection-based and Feature-Projection-based methods exhibit superior overall performance, while within Unified-Feature-based methods, the overall performance is more outstanding. In the meticulous evaluation of the KITTI and nuScenes datasets, emphasis is placed on the trade-off between FPS and NDS metrics.

3) **Robustness**: In the previous sections III-D3 and IV-E3, we analyzed the robustness of mono-modal 3D object detection (Camera-only and LiDAR-only). In this section, based on Tables IV and V, we analyze the robustness of multimodal 3D object detection. From KITTI-C [254] and nuScenes-C [254], it can be seen that multimodal 3D object detection is more robust compared to mono-modal 3D object detection

(Camera-only and LiDAR-only), with smaller RCE. In KITTI-C, representative articles LoGoNet [247] for Auto-Projection-based and VirConv [221] for Unified-Feature-based exhibit greater robustness, while EPNet [226] for Point-Projection-based and Focals Conv [232] for Feature-Projection-based show slightly weaker performance. Additionally, in nuScenes-C, among Non-Projection-based methods, FUTR3D [228], TransFusion [230], BEVFusion [231], and DeepInteraction [237] all demonstrate strong robustness.

VI. CONCLUSION

3D object detection plays a crucial role in autonomous driving perception. In recent years, this field has witnessed rapid development, yielding a plethora of research papers. Based on the diverse data forms generated by sensors, these methods are primarily categorized into three types: image-based, point cloud-based, and multimodal. The primary metrics for evaluation in these methods are high accuracy and low latency. Numerous reviews have summarized these approaches, focusing predominantly on the core principles of ‘high accuracy and low latency’ in delineating their technical trajectories. However, in the transition of autonomous driving technology from breakthroughs to practical applications, existing reviews have not prioritized safety perception as central concerns, failing to encompass the current technological pathways related to safety perception. For instance, recent multimodal fusion methods typically undergo robustness testing during the experimental phase, a facet not adequately considered in current reviews. Therefore, in this study, we reexamine 3D object detection algorithms with a central focus on the key aspects of ‘Accuracy, Latency, and Robustness.’ We reclassify previous reviews, placing particular emphasis on resegmenting from the perspective of safety perception. We aim for this work to offer new insights for future research in 3D object detection, transcending the confines of high-accuracy exploration.

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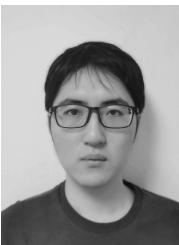
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