

Collaborative Perception in Autonomous Driving: Methods, Datasets and Challenges

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Abstract—Collaborative perception is essential to address occlusion and sensor failure issues in autonomous driving. In recent years, deep learning on collaborative perception has become even thriving, with numerous methods have been proposed. Although some works have reviewed and analyzed the basic architecture and key components in this field, there is still a lack of reviews on systematical collaboration modules in perception networks and large-scale collaborative perception datasets. The primary goal of this work is to address the abovementioned issues and provide a comprehensive review of recent achievements in this field. First, we introduce fundamental technologies and collaboration schemes. Following that, we provide an overview of practical collaborative perception methods and systematically summarize the collaboration modules in networks to improve collaboration efficiency and performance while also ensuring collaboration robustness and safety. Then, we present large-scale public datasets and summarize quantitative results on these benchmarks. Finally, we discuss the remaining challenges and promising future research directions.

Index Terms—Collaborative perception, autonomous driving, multi-agent communication, deep learning.

I. INTRODUCTION

AUTONOMOUS driving is a superior technology in research and commercial vehicles [1, 2, 3, 4, 5], with the potential to improve traffic efficiency, reduce traffic incidents and save resources. As the first stage of autonomous driving, perception is critical for vehicles to understand the environment. Significant progress [6, 7, 8, 9, 10, 11] has been made in autonomous driving perception with the breakthroughs of deep learning [12, 13, 14, 15, 16], however, developing a reliable autonomous driving perception system remains challenging.

For a long time, individual perception has dominated autonomous driving, which means the autonomous vehicle (AV) senses the surroundings using its own configured sensors and built-in network. Despite the rapid development of individual perception, some obstacles impede its expansion. Firstly, individual perception is always hampered by occlusion when perceiving a more comprehensive environment. Secondly, on-board sensors are physically limited, and sparse and low-resolution data in the long range make it challenging to detect distant objects. Furthermore, sensor noise also degrades the performance of the perception system. To compensate for

deficiencies in individual perception, collaborative or cooperative perception, which leverages the interaction between multiple agents to improve perception in autonomous driving, has received considerable critical attention.

Collaborative perception is a multi-agent system in which agents share perceptual information. According to the type of agents, it can be divided into V2V (vehicle-to-vehicle), V2I (vehicle-to-infrastructure), and V2X (vehicle-to-everything) modes. Collaborative perception is sometimes confused with sensor fusion (or multi-modal perception) [17, 18] as both contain the concept of sensor data fusion. It is noticeable that collaborative perception emphasizes the communication between multi-agents, however, conventional sensor fusion refers to the complementary sensors within the agent. To understand collaborative perception more intuitively, we provide an example of collaborative perception in autonomous driving. As shown in Fig.1, the point clouds generated by the ego vehicle have a limited range, and a portion of objects are in occluded and distant areas. As a result, the ego vehicle can only detect a part of the objects that are nearby and clearly visible. In a collaborative perception scenario, the ego vehicle receives information from other agents, such as autonomous vehicles or infrastructures. As the field of view expands and the sensor signal increases, the ego vehicle not only detects distant and occluded objects but also improves the detection accuracy in a dense area.

Collaborative perception has distinct advantages, but it also introduces new challenges. On the one hand, wireless communication has bandwidth limitations, achieving a tradeoff between accuracy and bandwidth while meeting real-time requirements is a difficult task. On the other hand, autonomous vehicles may encounter common and unavoidable problems in practice, such as localization error, communication latency and adversarial attacks. Thus, improving the robustness of collaborative perception systems is critical.

As deep learning methods have been widely applied to autonomous driving perception, efforts to improve the ability and reliability of collaborative perception systems are steadily increasing [19, 20, 21]. Besides, several publicly available datasets are released [22, 23, 24], which have further boosted the research on deep learning on collaborative perception in autonomous driving. With increasing research being proposed to address the above problems, it is necessary to summarize the advances in this field.

Several published notable surveys have discussed technologies in this field, such as [25, 26, 27, 28]. Yang et al. [25] build an entire intermediate collaborative perception system

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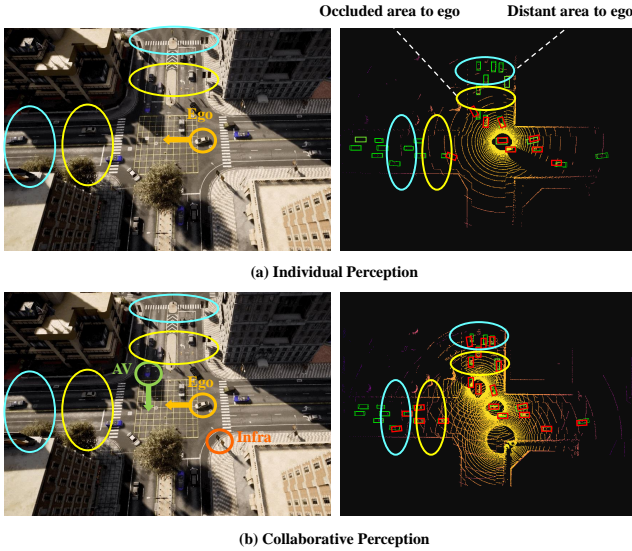


Fig. 1. Example of (a) individual perception and (b) collaborative perception in autonomous driving based on 3D point cloud. *Left*: Screenshot of one autonomous driving scenario. *Right*: Point cloud schematic. The green and red bounding boxes represent ground truths and predictions respectively. The yellow and blue ellipses represent occluded and distant areas of the ego vehicle. This example demonstrates collaborative perception’s impact on the ego vehicle’s visual range.

and discuss the collaboration challenges from different aspects, such as feature map selection, mmWave communications and vehicular edge computing. The fundamental concepts, the collaboration modes, key ingredients and applications of collaborative perception are summarized in [26]. Cui et al. [27] provide a comprehensive overview of collaborative methods mainly from the perspectives of sensor information fusion, information sharing strategies and communication technologies in the Internet of vehicles (IoV). Furthermore, Caillot et al. [28] introduce the architecture and facilities in a collaborative perception system and discuss three ego perception tasks based on a cooperative view.

Despite the thoroughness of these reviews, there are still knowledge gaps to fill. First of all, although previous works [27, 28] argue some key ingredients, there is still a lack of a systematical summary on collaboration modules in perception networks, making it difficult for researchers to understand the existing collaboration technologies intuitively. Secondly, the field of collaborative perception is evolving so fast that current reviews cannot cover the most recent research developments, resulting in the omission of numerous advanced strategies or newly proposed problems. Furthermore, preliminary efforts have been made on some of the challenges raised in the previous review [26, 27], such as communication delay[29], interruption[30] and attack[31], an overview is urgently needed to track these progress. Finally, once a bottleneck in this field, large-scale public datasets have also made a breakthrough recently. Nonetheless, with the exception of a few early small datasets mentioned in [28], there is no published summary examining available large-scale collaborative perception datasets.

Our work attempts to narrow the above gaps by reviewing methods and datasets of collaborative perception in autonomous driving and discussing the remaining challenges and

open questions. To track the latest progress and avoid duplication of summaries, we focus on **the most recent reproducible work**, and a milestone based on our research perspective is illustrated in Fig.2. Notably, our main contributions are highlighted below:

- We systematically summarize the collaboration modules in perception networks by reviewing the state-of-the-art methods. Specially, we argue the collaboration modules from two perspectives: *how to improve collaboration efficiency and performance* and *how to ensure collaboration robustness and safety*.
- Focused on collaborative perception scenarios, large-scale datasets, evaluation metrics and performance comparisons of typical methods are provided.
- Through a summary and discussion of existing methods, challenges and opportunities for collaborative perception in autonomous driving are presented.

This paper is structured as follows. Section II investigates basic technologies and section III presents collaboration scheme. Section IV systematically summarizes the collaboration modules in autonomous driving perception networks. We summarize well-referenced large-scale collaborative perception benchmark datasets and compare the performance of existing methods on these datasets in Section V. Open challenges and promising directions are discussed in Section VI. Finally, section VII provides a summary and concludes this work.

II. BASIC TECHNOLOGIES

This section provides the essential technologies for deep learning-based collaborative perception in autonomous driving. Considering collaborative perception is an application of a multi-agent system in autonomous driving perception, we introduce the multi-agent system and autonomous driving perception respectively. Firstly, we briefly describe the multi-agent system and its popular applications. Next, we present the typical visual sensors in autonomous driving and multiple autonomous driving perception methods.

A. Multi-Agent Systems

Multi-Agent System (MAS) is a distributed artificial intelligence [32, 33]. In MAS, agents interact with neighboring agents to learn new contexts. Subsequently, agents use knowledge to decide and perform an action. Such multi-agent systems have the advantage of increasing coverage of the environment or improving robustness to failures. The flexibility of MAS inspires Multi-Agent Reinforcement Learning (MARL) [2, 34, 35, 36], which aims to learn a policy for each agent so that all agents can achieve their goal together. In the past, MARL worked in autonomous driving focused on multi-agent interactions. CommNet [37] adopts average operation to fuse information of multi-agents, while VAIN [38] and ATOC [39] propose an attention-based communication model. Tarmac [40] introduces a strategy to select who to interact with actively.

Collaborative perception in autonomous driving is another application of a multi-agent system, intending to expand the

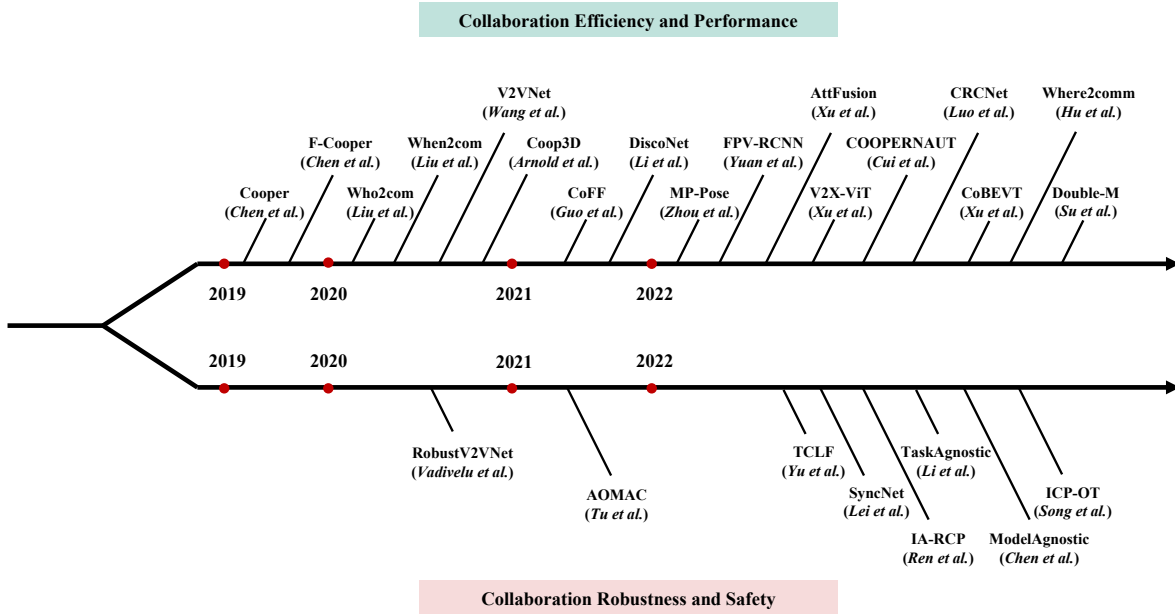


Fig. 2. A milestone of recent typical collaborative perception methods in autonomous driving. We illustrate these methods based on two perspectives: improving collaboration efficiency and performance and ensuring collaboration robustness and safety. Some of the work combines both, and we have categorized it according to its most prominent contribution.

ego agent’s view and improve self-driving perception capability. Theoretical and experimental studies of collaborative perception have increased dramatically in recent years. Cooper [41] and F-Cooper [42] propose the first early and intermediate collaboration, respectively. A batch of works is dedicated to improving the accuracy and robustness of collaborative perception systems.

B. Autonomous Driving Perception

Autonomous driving technology has a growing impact in research and application areas [1]. From a broad perspective, the autonomous driving system includes perception, planning, and control modules. The perception module utilizes sensors to continuously scan and monitor environments, which is critical to the overall driving system.

The perception module relies on multiple modalities. In general, autonomous vehicles employ different combinations of on-board sensors to perceive surroundings, and the most popular ones are RGB cameras and lidar:

- **RGB camera** is a low-cost sensor that provides detailed information in pixel intensities. RGB cameras could capture semantic information such as the texture and shape of objects. However, it lacks depth information, making it difficult to perceive 3D environments. In addition, the camera is susceptible to light and weather conditions, bringing enormous challenges to autonomous driving in complex scenes.
- **Lidar** is another standard sensor that generates point clouds, a sparse, irregular and continuous data structure. Lidar can capture 3D information and is immune to environmental conditions. Lidar has a broader field of view than cameras. Meanwhile, it also has disadvantages, such as expensive costs and lacking semantic information.

According to the type of sensor, autonomous driving perception can be divided into image-based, lidar-based and sensor fusion-based perception approaches [43]. Take 3D object detection as an example, image-based 3D object detection methods [7, 44] use images to predict the 3D bounding box, while it has a limited performance for lacking depth information. Point cloud-based methods [6, 45, 46, 47] usually employ different strategies to estimate bounding boxes, such as projecting point clouds into 2D pseudo images, establishing voxel representation, or processing raw data directly. Since point clouds contain rich 3D information, point cloud-based methods can achieve an ideal effect. To take full advantage of two types of sensors, some works [48, 49, 50] attempt to leverage sensor fusion to improve performance further.

Despite the rapid development of individual perception, it still suffers from occlusion and weak signals. To overcome these issues, collaborative perception [19, 20, 41, 42] is proposed and has become a new research hotspot. Simultaneously, collaborative perception has unique challenges, such as bandwidth limitation, localization error and latency. Focused on collaboration efficiency and challenges, this work presents an overview of recent techniques in collaborative perception.

III. COLLABORATION SCHEME

For a long time, traditional approaches to autonomous driving perception have focused on individual perception. The general pipeline of individual perception is that the network takes the data collected by sensors such as lidar or RGB camera as input, extracts features by an encoder and generates outputs based on task, as shown in Fig. 3 (a). In order to expand the view of the ego vehicle, collaborative systems share the pose information and perceiving data to the ego vehicle and combine the collaboration module into a perception network. The pose information is used to coordinate transformation

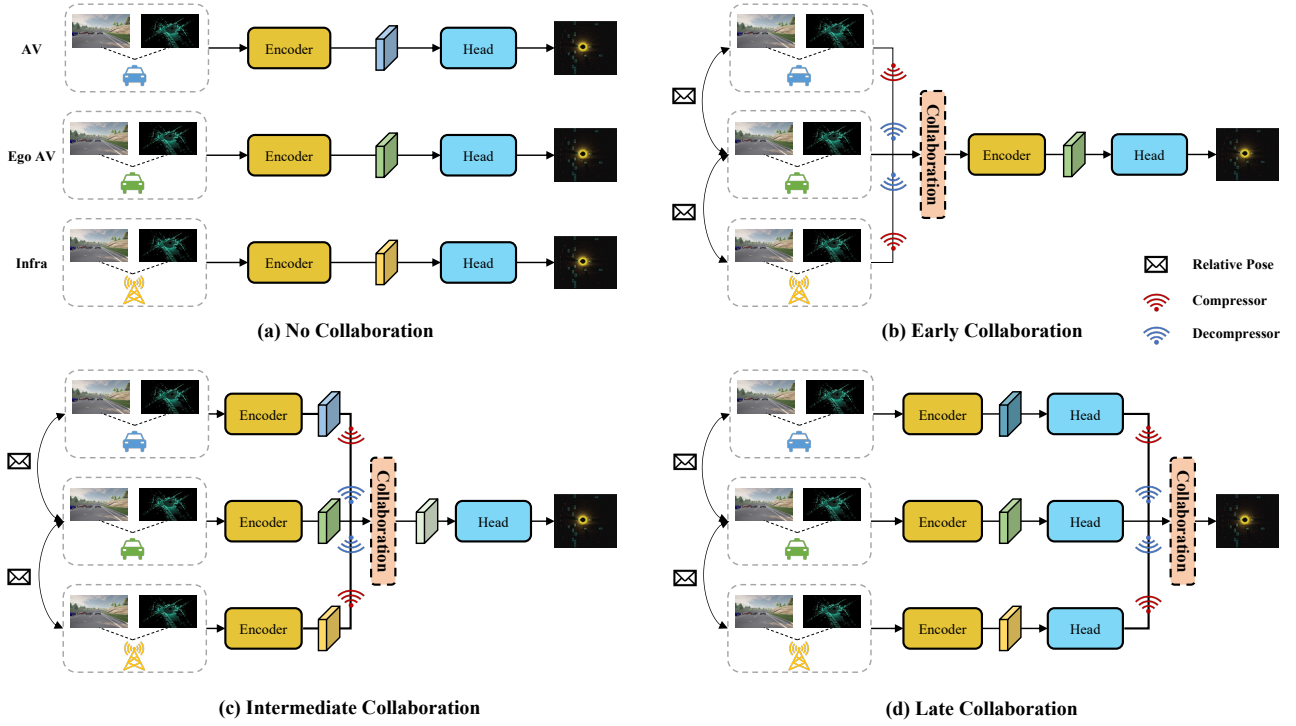


Fig. 3. The collaboration scheme indicates which phase performs data information interaction and fusion. (a) shows the pipeline of individual perception. The common agents include autonomous vehicles (AV) and infrastructures (Infra). (b-d) demonstrate three general frameworks of collaborative perception in autonomous driving. Early collaboration (b) transmits and fuses raw data at the input of the perception network, while intermediate collaboration (c) aggregates features, and late collaboration (d) merges outputs directly. All these collaboration systems require the relative position of neighbor agents to transform the sharing data to ego coordinate. Besides, a suitable data compression strategy is also necessary to meet transmission bandwidth constraints.

and the collaboration module is used to conduct specific fusion operations. According to the message delivered and the collaboration stage, the collaborative perception scheme can be broadly separated into early, intermediate, and late collaboration, as shown in Fig. 3 (b-d). It is worth noting that each agent can be an ego agent or a collaborative agent. We take an ego vehicle as an example to show the pipeline. Collaborative perception can be parallel in the actual scene.

A. Early Collaboration

Early collaboration employs the raw data fusion at the input of the network, which is also known as data-level fusion or low-level fusion, see Fig. 3 (b). Since the ego vehicle suffers from occlusion and limited views, raw sensor data sharing will overcome the above problems directly. In a collaborative autonomous driving scene, the ego vehicle selects neighbor vehicles or infrastructures within a limited distance, the selected agents will transfer the raw sensor data to the ego vehicle. Since the sensor data is taken on different positions and angles, the collaboration system need to transform them to the ego coordinates first and then aggregate transformed sensor data together, and the ego perception network will take the aggregation data as final input. Existing early fusion methods [41, 51] adopt point clouds as sensor data, and always aggregate point clouds directly.

Raw data contains the most comprehensive information and substantial description of agents. Consequently, early collaboration can fundamentally overcome occlusion and long-range

problems in individual perception and promote performance to the greatest extent. Early collaboration always becomes the upper bound of collaborative perception for its outstanding performance. However, early collaboration relies on high data bandwidth, which makes it challenging to implement in practice. Besides, the massive amount of raw data makes it difficult to achieve real-time edge computing.

B. Intermediate Collaboration

Considering the high bandwidth of early collaboration, some works [19, 20, 21, 23, 42] propose intermediate collaborative methods to balance the performance-bandwidth trade-off. Intermediate collaboration employs intermediate representations fusion in the feature learning phase, as shown in Fig. 3 (c). In intermediate collaboration, the ego vehicle and other agents usually utilize the same individual perception network and extract features respectively, and then collaborative agents will transfer their features to the ego vehicle. A compression strategy can be adopted to reduce transmission stress. After receiving transmitted features, the ego vehicle will use a transformation matrix to spatially transform features and then input these features to the collaboration module, which will update features to make the ultimate prediction.

Intermediate collaboration has become the most popular multi-agent collaborative perception choice for its low bandwidth requirements. Although features alleviate the bandwidth pressure, some information needed is lost and useless

or redundant data is introduced, which motivates people to present suitable feature selection strategies. Besides, deep representation makes the spatial relationship among agents more abstract and implicit, making exploring the relationship implied in features crucial.

C. Late Collaboration

Late collaboration or object-level collaboration [24, 51] employs the prediction fusion at the network output, as shown in Fig. 3 (d). Each agent infers the network individually and shares outputs (for example, bounding box in 3D object detection) with each other. The ego vehicle receives the results and spatially transforms the outputs. All outputs will be merged together after postprocessing.

Late collaboration is more bandwidth-economic and simpler than early and intermediate collaboration. However, the late collaboration also has limitations. Firstly, since individual output could be noisy and incomplete, late collaboration always has the worst perception performance. Secondly, late collaboration relies too heavily on single vehicular sensors and will only work when all agents share perception results. More seriously, late collaboration is sensitive to localization and time, which makes it hard to apply directly. A compromise way is to combine the late collaboration with the other two.

IV. COLLABORATIVE PERCEPTION METHODS

In this section, we provide a comprehensive review of recent collaborative perception approaches and systematically summarize the collaboration modules in perception networks, intending to give the researcher a more intuitive understanding of how the collaboration module works. Our perspectives are on improving collaborative efficiency and performance in ideal scenarios (Sec. IV-A) and ensuring collaborative robustness and safety in realistic autonomous driving scenes (Sec. IV-B). It is worth noting that some works take into account both perspectives. Tab.I provides a comprehensive overview containing related information on recent progress.

A. Improve Collaboration Efficiency and Performance

Due to bandwidth limitations and real-time requirements, a suitable collaborative strategy is essential to collaborative perception in autonomous driving. Different collaboration schemes require different strategies to improve collaborative efficiency and perception performance. The early and late collaboration fusion targets have clear physical meanings, and simple fusion and data compression strategies are sufficient [24, 41, 51]. In intermediate collaboration, considering deep semantic information contained in the shared features, the reasonable feature selection [52, 53] and fusion strategies [19, 20, 21] are required. Besides, the collaboration among agents will bring redundant and uncertain information. Accordingly, it is necessary to capture this latent information [29, 54]. Because existing collaborative perception methods are built with different collaboration modules and diverse strategies, we summarize these modules according to their stage, as shown in Fig.4.

1) *Point Cloud Fusion*: Early collaboration adopts data fusion at the input stage. Since point clouds are easily aggregated, recent works [41, 51] usually introduce point cloud fusion strategies.

Chen et al. [41] propose the first early collaborative perception system Cooper. Cooper chooses lidar data as a fusion target for its providing location information. By only extracting positional coordinates and reflection values, point clouds can be compressed into smaller sizes. After receiving sensor data from neighbor agents, Cooper applies a transform to the original coordinates so that sensor data can match the state of the receiving vehicle. Then ego vehicle concatenates the set of ego point clouds and transformed point clouds. Finally, the aggregated point clouds will be fed into the perception network. Experiments show that the Cooper system outperforms individual perception by extending the sensing area.

Inspired by Cooper [41], Arnold et al. [51] also explore early collaboration. Specifically, early collaboration utilizes a new spatial transformation equation, which is different from Cooper that employs concatenation to fuse sensor data. Unlike Cooper sharing vehicle-to-vehicle information on board, Arnold et al. [51] propose a central system Coop3D to merge multiple sensor data, which allows for amortization of both sensor and processing costs in collaboration. Considering the different advantages of early and late collaboration, Coop3D adopts a hybrid collaboration strategy to take full advantage of both schemes. The key concept is to share high-level information where the sensor has high visibility and share low-level information where the visibility is poor.

2) *Feature Selection*: To alleviate the high bandwidth consumption in early collaboration, more and more works [19, 20, 21] develop feature-level collaboration. Intermediate collaboration networks extract and select feature representations into collective perception messages (CPMs) in the base network stage. In order to provide as much spatial information as possible, the initial intermediate collaboration frameworks select and compress the full feature maps into CPMs. However, the irrelevant information hugely wastes the bandwidth and degrades the perception performance. To fill this gap, some works [52, 53] consider remarkable feature selection strategy.

Yuan et al. [53] propose a robust collaboration framework FPV-RCNN by extending a two-stage 3D object detection network PV-RCNN [47]. Specifically, FPV-RCNN selects key points and calculates their features after proposal generation, only the feature points in the proposals can be selected. Keypoints selection module reduces the redundancy of shared deep features so as to decrease communication pressure, and further provides valuable supplementary information to initial proposals. Compared with BEV keypoints fusion, FPV-RCNN with reduced communication overhead still achieves higher detection accuracy.

Where2comm [52] also considers a novel spatial-confidence-aware communication strategy, and the core idea is to utilize a spatial confidence map to decide where and to who to communicate. In the feature selection module, Where2comm only selects spatial features which satisfy high confidence and high request and then transmit the non-zero

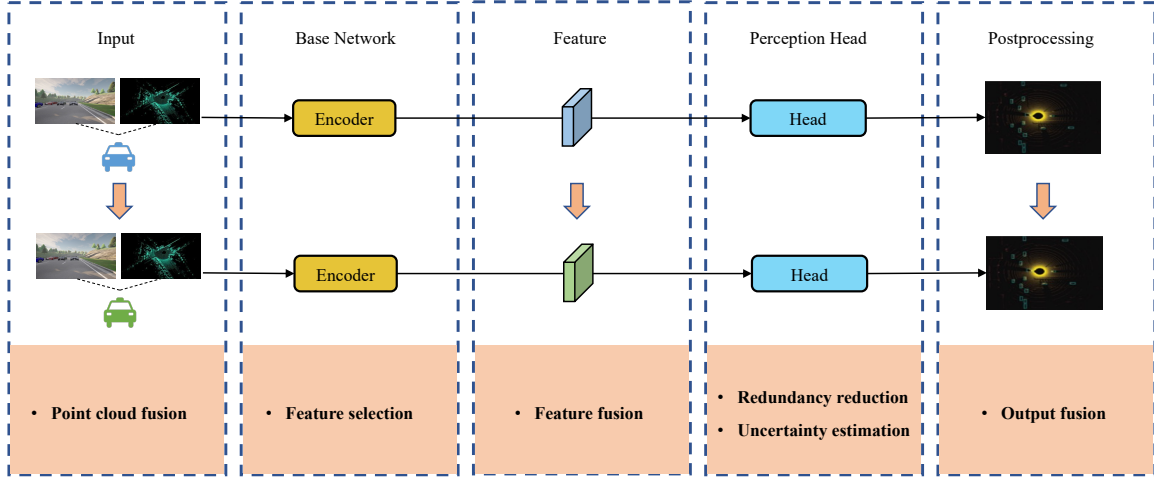


Fig. 4. Illustration of the critical collaboration strategies present in typical collaborative perception networks, which are used to improve collaboration efficiency and performance. Common collaboration strategies include point cloud fusion (input stage), feature selection (base network stage), feature fusion (feature stage), redundancy reduction and uncertainty estimation (perception head) and output fusion (postprocessing stage). Various approaches will choose the best collaboration strategy based on the collaboration scheme and objectives, and some strategies can be combined. To more thoroughly summarize the collaboration module, we will discuss the corresponding collaboration strategy based on the perception network stage of these blocks.

features and corresponding indices. By sending and receiving the features on perceptually critical areas, Where2comm can save massive bandwidth and make the collaborative features more relevant.

3) *Feature Fusion*: Feature fusion module is the crucial ingredient in intermediate collaboration. After receiving CPs from other agents, the ego can leverage different strategies to aggregate these features in the feature stage. A feasible fusion strategy can complete effective information complementation and redundant information removal and improve perception performance.

a) *Traditional Collaboration*: At the early stage of the research on collaborative perception, people tend to use traditional strategies to fuse features. These intermediate collaboration applies the permutation invariant operations on deep features [42, 55].

Chen et al. [42] introduce the first intermediate collaborative perception framework F-Cooper. [42] extracts low-level voxel feature with Voxel Feature Encoding (VFE) layer and deep spatial feature with Feature Learning Network (FLN) [45]. Based on two level features, Chen et al. [42] propose two feature-fusion strategies: Voxel Feature Fusion (VFF) and Spatial Feature Fusion (SFF), and both of them employ element-wise maxout scheme [56] to fuse features in overlapped regions. The maxout function can be represented as Eq. 1, where F_1 and F_2 are features in overlapping areas from the receiver and the sender, F_3 is the nonoverlapping area of the ego feature map. Since voxel features are closer to raw data, VFF is as capable as the raw data fusion method for near object detection. Although SFF is not good as VFF for its low-resolution spatial features, it has its own advantage. Inspired by SENet [57], SFF opts to select partial channels to transport, which can further reduce the time consumption of transmission while keeping the comparable detection precision.

$$\mathbf{F} = \{\mathbf{F}_3 \cup \max\{\mathbf{F}_1, \mathbf{F}_2\}\} \quad (1)$$

Maxout strategy in F-Cooper [42] essentially keeps larger values of two feature maps and ignores smaller ones, which cannot capture the importance of weak features or enhance the weak feature. To address the above limitations, Guo et al. [55] propose CoFF approach. In essence, CoFF weights the overlapped features by measuring their similarity and overlapping area. The smaller the similarity and the greater the distance means the more supplementary information provided by neighbor features intuitively. Besides, an enhancement parameter is added to increase the value of weak features. The CoFF approach can be presented as Eq. 2. where X represents the semantic information measurement and Y represents the feature enhancement parameter. Experiments show that CoFF improves F-Cooper [42] much.

$$\mathbf{F} = \{\mathbf{F}_3 \cup \max\{\mathbf{F}_1, \mathbf{F}_2 \times X\}\} \times Y \quad (2)$$

b) *Graph-based Collaboration*: Despite the simplicity of traditional intermediate collaboration methods [42, 53, 55], they ignore the relationship among multi-agents and fail to jointly reason the messages from sender to receiver. Graph Neural Networks (GNNs) have the ability to process graph-structured data, which can propagate and aggregate messages from neighbors [58]. Recent works have shown the effectiveness of GNN on perception [59, 60, 61] and autonomous driving [62, 63]. When we regard the agents and the connection as nodes and edges respectively, the collaboration of agents becomes a graph structure naturally. Some works believe GNNs are tailored for V2V communication and leverage GNNs to aggregate messages between agents [19, 20, 64]. The primary stages of GNN are message passing and message aggregation. Therefore, we introduce graph-based collaboration methods based on these two stages.

Wang et al. [19] firstly leverage a spatial-aware graph neural network (GNN) to model the communication among agents and derive V2VNet. The key insight is that collabo-

ration among vehicles can enhance the representation of the overlapping area. In GNN message passing stage, V2VNet utilizes a variational image compression algorithm [65] to compress intermediate representations. In cross-vehicle aggregation, V2VNet first compensates for the time delay to create an initial state for each node, and then warps and spatially transforms the compressed features from neighbor agents to ego vehicles, which is conducted in overlapping fields of view only. Features are accumulated by average operation and the node state is updated with a convolutional gated recurrent unit (ConvGRU). V2VNet achieves the compromise between accuracy improvements and bandwidth requirements, while it claims three rounds to ensure reliable performance.

Although V2VNet [19] achieves progress with GNN, the collaboration weight is a scalar, which cannot reflect the importance of the different regions. Motivated by this, Li et al. [20] propose DiscoNet, which utilizes a matrix-valued edge weight to capture the inter-agent attention in high resolution. During the message passing, DiscoNet warps features and learns the matrix-valued edge weight for each element in feature maps, and finally aggregates multi-agents features with the channel-wise products. With the matrix-weight design, DiscoNet can capture spatial information at high resolution. Besides, DiscoNet combines the early fusion and intermediate fusion together by applying a teacher-student framework, which further improves the performance of DiscoNet.

Zhou et al. [64] propose another generalized GNN-based perception framework MP-Pose. During the message passing stage, MP-Pose encodes the relative spatial relationship with a spatial encoding network rather than warps features directly [19, 20]. Inspired by Graph Attention Networks (GAT) [66], it further uses a dynamic cross attention encoding network to capture the relationship of agents, and aggregate multiple features followed GAT. Like DiscoNet, MP-Pose doesn't consider asynchronism and pose error problems.

c) Attention-based Collaboration: Attention is another helpful tool, which can be regarded as a dynamic weight adjustment process based on features. According to the data domain, attention mechanisms contain channel attention, spatial attention and channel & spatial attention [67]. Based on the operation target, attention mechanisms contain self-attention and cross-attention [68]. In the past decade, the attention mechanism has played an increasingly important role in computer vision [13, 57, 69, 70], which also inspires collaborative perception research. Since feature selection and relationship exploring are vital issues in intermediate collaborative perception, some works [21, 23, 29, 71, 72, 73, 74] leverage attention mechanisms to exploit more dynamic and robust collaborative perception strategies. Due to flexibility, attention-based design becomes the dominant strategy in intermediate collaboration.

In order to choose the best matching agents, Liu et al. [71] firstly propose an attention-based collaborative perception framework Who2com. Inspired by three-way handshaking in network communication, Who2com [71] adopts a three-stage communication mechanism: request, match and connect. Specifically, request and match stages determine the agents that need to interact with, and they use a general attention function [75] to calculate match scores among ego agents and

match agents. As shown in Eq.3, μ_i is the ego observation and κ_j is the request message from other agents, \mathbf{W} is a learnable parameter in general attention. In connect stage, Who2com will concatenate all features to update the ego feature. Who2com is a flexible attention-based framework for its allowing different key and message sizes in the match stage, besides, selecting the most needed agents to reduce bandwidth effectively.

$$\begin{aligned} \mathbf{m}_{i,j} &= \Phi(\mu_i, \kappa_j), \quad \forall i \neq j \\ \Phi(\mu_i, \kappa_j) &= \mu_i^T \mathbf{W} \kappa_j \end{aligned} \quad (3)$$

Who2com [71] uses a general cross-attention to determine who to communicate with, while it assumes the communication is continuous and it's a waste of bandwidth consumption. To overcome this limitation, Liu et al. [72] propose When2com to decide when to communicate. Inspired by the self-attention mechanism [68], When2com introduces scaled general attention for the ego agent to determine when to communicate. The self-attention is shown as Eq. 4, match function Φ is similar to that in Who2com, and the added K is the dimension of the key vector. Match score $\mathbf{m}_{i,i} \approx 1$ represents ego has sufficient information and does not need collaboration.

$$\begin{aligned} \mathbf{m}_{i,i} &= \Phi(\mu_i, \kappa_i) \\ \Phi(\mu_i, \kappa_j) &= \frac{\mu_i^T \mathbf{W} \kappa_j}{\sqrt{K}} \end{aligned} \quad (4)$$

Previous attention-based collaboration methods [71, 72, 73] utilize attention operation on the whole feature vector, ignoring the interaction among the certain area of the feature map. On the contrary, Xu et al. [23] propose AttFusion and firstly employ self-attention operation [68] at the same spatial location in multi-agents feature maps. The idea of spatial-aware interaction is similar to matrix-weight edge in DiscoNet [20], while they are implemented with different tools.

Besides traditional attention-based methods, Transformer-based methods also inspire collaborative perception. Cui et al. [76] propose COOPERNAUT based on Point Transformer [77], a self-attention network for point cloud processing. After receiving messages, the ego agent uses a down-sampling block and point transformer block to aggregate points features. The former block is used to reduce the cardinality of the point sets, and the second block allows local information exchange among all points. Both two operations preserve the permutation invariance of messages. What is more important, COOPERNAUT integrates collaborative perception with control decisions, which is of great significance for the module linkage of autonomous driving.

Compared with V2V collaboration, V2I could provide more stable collaboration information with a huge amount of infrastructure, whereas there have few works have paid attention to this scenario. To fill this gap, Xu et al. [21] present the first unified transformer architecture (V2X-ViT) for V2X perception, which covers V2V and V2I simultaneously. In order to module interactions among agents, V2X-ViT proposes a novel heterogeneous multi-agent attention module

(HMSA). HMSA learns different relationship between V2V or V2I. Furthermore, MSwin is introduced to capture long-range spatial interaction on high-resolution detection. The concept of heterogeneity in this paper [21] has a great inspiration for subsequent research.

RGB camera is a more general and cheaper modality compared with lidar, while little research has concentrated on image-based perception. Though Who2com [71] and When2com [72] conduct experiments with images, they are not in the autonomous driving scenarios. To fill this gap, [78] presents the first generic multi-camera-based collaborative perception framework CoBEVT. Considering the interaction among multi-view and multiple agents, CoBEVT designs fused axial attention (FAX) module to perform both sparse global interactions (cross-attention), which is used to capture the interactions among multi-cameras and local window-based attention (self-attention), which is used for multi-agent information fusion. Experiments demonstrate that CoBEVT performs well in both multi-view and multi-agent interaction, moreover, it is robust to camera dropout.

4) *Redundancy Reduction and Uncertainty Estimation:* Though V2V communication provides a relatively rich perceptual field of view for the ego vehicle, the redundancy and uncertainty of shared information bring new challenges to collaborative perception. To overcome these issues, the guidance of model training in perception head stage is also significant.

In the collaboration scene, nearby neighbor agents may provide similar information which is redundant to the ego vehicle in the autonomous driving scenario. To minimize this redundancy, Luo et al. [29] propose a complementarity-enhanced and redundancy-minimized collaboration network (CRCNet). In the feature fusion stage, CRCNet incorporates channel-wise [79] and spatial-wise attention to select and fuse features. In the training phase, CRCNet designs two modules to guide the network. On the one hand, the enhancement of information gain can enhance feature complementarity. Inspired by contrastive learning [80, 81], extra information gain brought by collaboration is expressed by the difference of ego classification loss before and after fusion, as shown in Eq.5, where $L_{cls}(p_j^n(\mathbf{P}_i), y_j^n)$ is the loss function before fusion, $L_{cls}(p_j^n(\mathbf{P}_i + T_i^k), y_j^n)$ is the loss function after fusion, and δ_k is information gain of collaboration. On the other hand, to reduce the redundancy of fused features, CRCNet leverages mutual information [82] to encourage the dependence in fused feature pairs, as shown in Eq.6. The combined use of two modules gives CRCNet a comparable performance.

$$\delta_k = \sum_n L_{cls}(p_j^n(\mathbf{P}_i), y_j^n) - \sum_n L_{cls}(p_j^n(\mathbf{P}_i + T_i^k), y_j^n) \quad (5)$$

$$L_{red} = \sum_k \sum_l [\log q_{\theta_2}(T_i^l/T_i^k) - \log q_{\theta_2}(T_i^l/T_n^k)] \quad (6)$$

Besides redundancy, the connected autonomous vehicle also contains perceptual uncertainties, which reflect perception

inaccuracy or sensor noises. Su et al. [54] firstly explore the uncertainty in collaboration perception. Specifically, they design Double-M Quantification tailors moving block bootstrap to estimate both the model and data uncertainty, together with a well-designed direct modeling component. Experiments reveal that uncertainty estimation could reduce uncertainty and improve accuracy in different collaboration schemes.

5) *Output Fusion:* Late collaboration usually adopts fusion operation at the postprocessing stage, which merges perception outputs of multi-agents together. The most common late fusion strategy is leveraging postprocessing methods such as Non-Maximum Suppression (NMS) [83] to remove redundant and low-confidence prediction. However, late fusion always faces challenges such as spatial and temporal misalignment, some works [24, 84] propose more robust postprocessing strategies to refine late fusion methods. The relevant methods will be summarized in the next subsection.

B. Ensure Collaboration Robustness and Safety

Most previous collaborative perception research [19, 20, 23, 42] focuses on collaboration efficiency and perception performance, but all of these methods assume perfect conditions. In real-world driving scenarios, the communication system inevitably suffers from some issues, such as localization error caused by GPS, possible latency and interruption in communication, model or task discrepancies and adversarial attack, resulting in potential performance degradation and high risks in autonomous driving. We summarize the issues that commonly arise at various stages of the collaborative perception, as shown in Fig.5. With these issues, the collaborative perception system may be damaged and perform even worse than single-agent perception, which will seriously threaten autonomous driving safety. Therefore, it is of great practical significance to ensure robustness and safety for collaboration perception. In this subsection, we focus on advanced research on these issues and summarize collaborative modules designed to address these issues [21, 24, 31, 53, 74, 85, 86].

1) *Localization Error:* As discussed in the collaboration scheme, collaborative perception methods rely on spatial transformation, which is used to transform raw data, features or outputs. However, localization errors are common. Both GPS localization noises and the asynchronous sensor measurements of agents can introduce localization errors, resulting in data misalignment during aggregation and a significant reduction in collaborative perception system performance. Research [21, 53, 85] always employs a variety of pose consistency modules to address this issue.

Experiments have shown that the novel collaborative perception method V2VNet [19] is quite vulnerable to pose noise and performs worse than individual perception under pose noise. To tackle localization error issues, Vadivelu et al. [85] introduce end-to-end learnable neural reasoning layers to correct pose errors. Specifically, [85] proposes a pose regression module and consistency module before feature aggregation. The pose regression module learns a correction parameter, which will be applied to the noisy relative transformation to produce a predicted true relative transformation. The consistency module further refines the predicted relative pose by

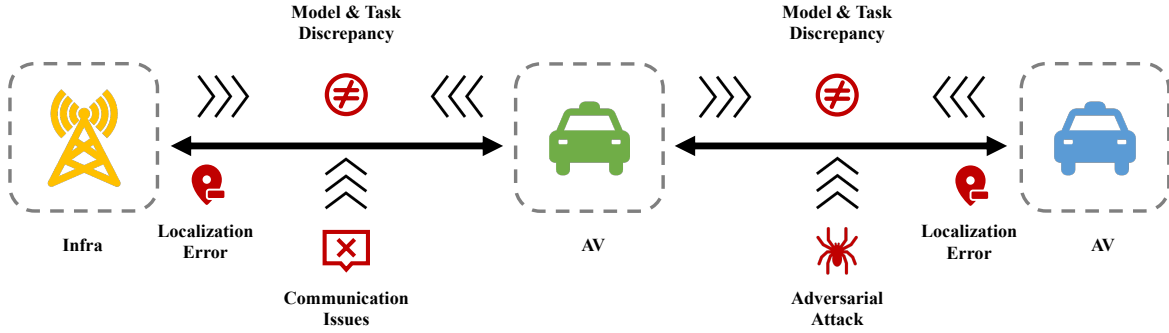


Fig. 5. Illustration of the collaboration issues in realistic scenarios. Since coordinated vehicles will encounter some unavoidable issues, such as GPS-induced localization errors, information latency and corruption in communication, model or task discrepancies, and the adversarial attack on sharing feature. Many works have been dedicated to ensuring collaboration robustness and safety, We have summarized collaboration modules to alleviate these issues.

finding a global consistent absolute pose among all agents with Markov random field (MRF). Furthermore, in order to suppress the error prediction, [85] proposes a simple yet effective attention mechanism to assign each warped feature a weight. A combination of three modules gives RobustV2VNet a robust and excellent performance even under high-pose noise.

Yuan et al. [53] also propose an effective localization error correction module to avoid the performance reduction under localization error. FPV-RCNN selects keypoints of poles, fences and walls based on the classification score at the first stage, and utilizes the maximum consensus algorithm with a rough searching resolution to find the corresponding vehicles centers and poles points, and final use correspondence [87] to estimate pose error. Experiments demonstrate that FPV-RCNN performs better than traditional BEV-based collaboration methods with localization errors.

Late collaboration methods usually adopt simple and straightforward fusion strategies, accordingly, they are more sensitive to this error. To realize robust object-level information combination, [84] designs Iterative Closest Point (ICP)-based and Optimal Transport (OT)-based algorithms to explore fine matching between objects. With the refinement module, the late collaboration could get a relatively accurate performance even with high location and heading errors.

Similar to ICP-OT[84] that explore pose consistency with object matching algorithms, Lu et al. [88] propose a pose graph optimization to estimate the correct poses. With the idea of aligning the corresponding bounding boxes of the same object,[88] construct an agent-object pose graph. Specifically, the object nodes are spatially clustering. The object pose is sampled from the bounding box cluster, and a pose-consistency optimization function is introduced. With this pose correction module, the collaboration perception network achieves significant performance in various noise levels.

2) *Communication Issues*: Since collaborative perception relies on communication networks, communication issues such as latency, interruption and information loss also affect the effectiveness of collaboration. In recent years, several efforts [21, 24, 74] have begun to explore solutions to these problems.

To tackle the latency issue in late collaboration, Yu et al. [24] propose a Time Compensation Late Fusion (TCLF) framework based on tracking and state estimation module.

TCLF predicts the current infrastructure prediction with the previous adjacent frame. By matching predictions of the adjacent frame, TCLF can estimate the object velocity and further approximate the object positions at the current frame by linear interpolation. Finally, the estimated infrastructure predictions will be fused with ego prediction. TCLF is an effective post-processing strategy to tackle latency issues, whereas it is not an end-to-end learnable method.

Compared with TCLF [24], V2X-ViT [21] mitigates latency in intermediate collaboration. In particular, V2X-ViT leverages an adaptive delay-aware positional encoding module (DPE) to align features temporally. Moreover, the HMSA and MSwin modules capture inter and intra-agents interactions, which can implicitly correct feature misalignment caused by localization error and time delay. Experiments show that DPE can improve performance under various time delays.

Furthermore, Lei et al. [74] proposes the first latency-aware collaborative perception system, which realizes a feature-level synchronization. Considering feature and attention are closely linked and influence each other, the core module SyncNet estimates the coupling of collaborative feature and attention simultaneously. In the feature-attention symbiotic estimation (FASE) module, dual branches share the same input, which contains real-time and historical features, and learn interactions from previous features/attention and estimated features/attention in turn. Furthermore, time modulation adaptively fuses the raw feature and estimated feature based on latency time. In the training phase, Lei et al. [74] design an appropriate strategy to train SyncNet, and the proposed compensation module consistently and significantly benefits existing frameworks.

In addition to latency, Ren et al. [30] firstly considers the communication interruption in collaborative perception. To alleviate the effect, [30] leverages the historical information to recover missing features and propose an interruption-aware robust collaborative perception (IA-RCP) framework. In addition, they introduce a spatial attention mask to suppress background noise and adopt a curriculum learning strategy to stabilize training.

Packet loss is also a critical problem in communication, which may be caused by obstacles and fast-moving vehicles. To address this issue, Li et al. [89] proposes LC-aware Repair Network (LCRN) ensure the robustness of collaborative

perception under lossy communication. Inspired by image-denoising architecture, LCRN adopts an encoder-decoder architecture with a repair loss to recover features from other agents. Moreover, Li et al. [89] presents an attention-based fusion method to fuse features with inter and intra-agents to eliminate uncertainty in restoration features, further enhancing the model’s robustness.

3) *Model & Task Discrepancies*: Existing multi-agent collaborative perception methods usually learn in a model-specific and task-specific manner, assuming each agent utilizes the same models to predict outputs for specific perception tasks. However, homogeneous models in multi-agents are impractical in the real world, and task-specific training will lead to task-specific information, which hinders the large-scale deployment of collaborative perception. To mitigate discrepancies in models or tasks, some works provide solutions from a new perspective.

The model discrepancy is an actual problem in the real world. When distinct agents are equipped with perception models in different architectures and parameters, current collaboration methods may generate unreliable fusion results due to model heterogeneity. To alleviate this issue, Chen et al. [86] propose a model-agnostic collaborative perception framework. Firstly, considering there is a confidence distribution among different agents, an offline calibrator is used to align the confidence score of agents to its empirical accuracy. Additionally, to conduct collaboration with the spatial correlation, [86] presents Promotion-Suppression Aggregation (PSA) module, which leverages an Intersection-over-Union (IOU) graph to find promotion proposals. The whole process is safe because the structure and parameters of the models are not touched. Future work is encouraged to explore the relations in heterogeneity.

The task discrepancy is another valuable issue. Task-specific training will endow model task-adapted feature extraction capabilities. However, the extracted feature is not suitable for other tasks. The deployment of autonomous driving collaborative perception involves multiple tasks, thus requiring models to capture general and robust features. To this end, Li et al. [90] propose a novel self-supervised learning task termed collaborative scene (CSC), which enables each agent to reconstruct a single scene separately to learn latent features. Specifically, Li et al. [90] design a spatio-temporal-aware autoencoder (STAR) module to balance the scene reconstruction performance and communication volume in this task. The model learns more robust representations for multi-tasks with the novel autoencoder.

4) *Adversarial Attack*: Collaborative perception relies on communication between agents, while the shared information may be malicious and the network in agents is vulnerable to adversarial attacks. In practice, even small perturbations can make severe predictions. By studying adversarial robustness, we can enhance the security of collaborative perception. Up to now, there is just one work [31] that investigates adversarial attacks in collaborative perception. Tu et al. [31] mainly design a novel transfer attack approach in the intermediate collaborative perception. Since we focus on robustness here, we only discuss the impact of the attack and the defense

strategy rather than the adversarial attack establishment.

Tu et al. [31] evaluate the attack and defense performance on V2VNet[19] for V2V collaboration scenario. From the perspective of attack, the coordination of attacks generates a stronger attacker. From the defense perspective, if the attack model is known, adversarial training can effectively defend against the attack. When the knowledge of the attack model cannot be required, a feasible design of the feature collaboration strategy is necessary. Besides, as the number of collaboration agents increases, the defense ability of the collaboration system is enhanced. So far, no work has been devoted to defense mechanisms against attacks. Further research should be conducted to fill this gap.

V. DATASETS AND EVALUATION

Large open datasets, which are required for deep learning, were previously a bottleneck in the development of collaborative perception. Although there are many mature self-driving datasets available, such as KITTI [95], nuScenes [96] and Waymo [97], they focus on individual perception and cannot meet the demand for collaborative perception. Fortunately, recent advances in large-scale benchmark [22, 23, 24] for collaborative perception have accelerated the development of autonomous driving visual tasks like detection, segmentation and tracking.

We summarize existing collaborative perception datasets in Tab.II, and provide comparisons on scenarios and sensors, etc. In particular, we examine some popular datasets and benchmarks and select the two typical perception tasks in autonomous driving to further evaluate the performance of some mainstream collaborative perception methods. Considering that research for solving robust problems adopts different experimental setups, it is difficult to make a fair comparison. Thus, only a subset of the experimental results for ideal scenarios are presented in this paper.

A. Large Scale Public Collaborative Perception Datasets

Due to the difficulty of collecting data in reality, most of the collaborative perception datasets are generated by simulation [21, 22, 23], and only a few are collected from real-world [24]. In this subsection, we introduce several typical datasets that meet the following conditions: (1) open source, (2) large-scale datasets and (3) providing benchmarks that can be followed. We will analyze the characteristics of these datasets to facilitate the researcher’s selection.

1) *V2X-Sim*: V2X-Sim [20, 22] is a comprehensive simulated multi-agent perception dataset. It is generated with traffic simulation SUMO [100] and CARLA simulator[101], and the data format follows nuScenes [96]. Equipped with RGB cameras, Lidar, GPS and IMU, V2X-Sim collects 100 scenes with a total of 10,000 frames, each scene contains 2-5 vehicles. Frames are divided into 8,000/1,000/1,000 for training/validation/testing. The benchmark of V2X-Sim supports three crucial perception tasks: detection, tracking and segmentation, it should be noted that all tasks adopt a bird’s-eye-view (BEV) representation and generate results in 2D BEV.

TABLE I
A SUMMARY OF STATE-OF-THE-ART COLLABORATIVE PERCEPTION METHODS.

Method	Year	Publication	Collab Scheme*	Collab Blocks*	Collab Issues†	Dataset	Code
Cooper [41]	2019	ICDCS	E	PCF	-	KITTI,T&J	-
F-Cooper [42]	2019	SEC	I	FF(T)	-	KITTI,T&J	Link
Who2com [71]	2020	ICRA	I	FF(A)	-	AirSim-CP	-
When2com [72]	2020	CVPR	I	FF(A)	-	AirSim-CP	Link
V2VNet [19]	2020	ECCV	I	FF(G)	-	V2V-Sim	-
RobustV2VNet [85]	2020	CoRL	I	FF(A)	Loc	V2V-Sim	-
Coop3D [51]	2020	TITS	E,L	PCF,OF	-	CoopInf	Link
FS-COD [91]	2020	VTC	I	FF(T)	-	-	-
CoFF [55]	2021	IoT	I	FF(T)	-	KITTI,T&J	-
DiscoNet [20]	2021	NeurIps	I	FF(G)	-	V2X-Sim	Link
FAR [73]	2021	RAL	I	FF(A)	-	KITTI, CODD	Link
AOMAC [31]	2021	ICCV	I	FF(G)	Attack	V2V-Sim	-
MP-Pose [64]	2022	RAL	I	FF(G)	-	Airsim-MAP	-
FPV-RCNN [53]	2022	RAL	I	FS,FF(T)	Loc	COMAP	Link
Attfusion [23]	2022	ICRA	I	FF(A)	-	OPV2V	Link
TCLF [24]	2022	CVPR	L	OF	Comm(La)	DAIR-V2X	Link
COOPERNAUT [76]	2022	CVPR	I	FF(A)	-	AUTOCASTSIM	Link
V2X-ViT [21]	2022	ECCV	I	FF(A)	Loc,Comm(La)	V2XSet	Link
SyncNet [74]	2022	ECCV	I	FF(A)	Comm(La)	V2X-Sim	Link
IA-RCP [30]	2022	IJCAI	I	FF(A)	Comm(In)	V2X-Sim	-
CRCNet [29]	2022	MM	I	FF(A),RR	-	V2X-Sim	-
CoBEVT [78]	2022	CoRL	I	FF(A)	-	OPV2V, nuScenes	Link
Where2comm [52]	2022	NeurIps	I	FS,FF(A)	Loc	OPV2V,V2X-Sim,DAIR-V2X	Link
TaskAgnostic [90]	2022	CoRL	I	-	Discrep	V2X-Sim	-
AdaFusion [92]	2022	WACV	I	FF(A)	-	OPV2V, CODD	-
ModelAgnostic [86]	2022	-	L	FF(T)	Discrep	OPV2V	-
Learn2com [93]	2022	-	I	FF(A)	-	-	-
CO ³ [94]	2022	-	E	FF(T)	-	DAIR-V2X-C	-
ICP-OT [84]	2022	-	L	OF	Loc	OPV2V	-
Double-M [54]	2022	-	E,I,L	FF,UE	Loc	V2X-Sim	Link
CoAlign [88]	2022	-	I	FF(A),UE	Loc	OPV2V,V2X-Sim,DAIR-V2X	Link
LCRN [89]	2022	-	I	FF(A)	Comm(Lo)	OPV2V	-

Collab Block: Basic modules to improve collaboration efficiency and performance, Collab Issues: Some problems exist in the real world.

* E: Early, I: Intermediate, L: Late

* PCF: Point cloud fusion, FS: Feature selection, FF: Feature fusion (T: Traditional, G: Graph, A: Attention), RR: Redundancy reduction, UE: Uncertainty estimation, OF: Output fusion

† Loc: Localization error, Comm: Communication issues (La: Latency, In: Interruption, Lo: Loss), Discrep: Model & Task discrepancies, Attack: Adversarial attack

2) *OPV2V*: *OPV2V* [23] is another simulated collaborative perception dataset for V2V communication, which is collected with the co-simulating framework *OpenCDA* [102] and *CARLA* simulator [101]. The whole dataset is reproducible with provided configuration files. *OPV2V* contains 11,464 frames with Lidar points and RGB cameras. A worthy characteristic is that it provides a realistic imitating test set called *Culver City*, which can be used to evaluate the generalization of the model. Benchmark supports 3D object detection and BEV semantic segmentation. It is noticeable that so far the dataset contains only one type of object (vehicle).

3) *DAIR-V2X*: As the first large-scale V2X collaborative perception dataset from real scenarios, *DAIR-V2X* [24] is significant to collaborative perception for autonomous driving. *DAIR-V2X* comprises 71254 lidar frames and 71254 camera

frames, all of which are captured from real scenes with 3D annotations. *DAIR-V2X-C* set can be used to study V2X collaboration and the *VIC3D* benchmark is provided to explore V2X object detection tasks. Different from *V2X-Sim* [22] and *V2XSet* [21] that mainly focus on lidar points, the *VIC3D* object detection benchmark provides both image-based and lidar points-based collaboration methods.

4) *V2XSet*: *V2XSet* [21] is a large-scale open simulation dataset for V2X perception. The dataset format is similar to *OPV2V* [23] and there are 11,447 frames in total. Compared with V2X collaboration datasets *V2X-Sim* [22] and *DAIR-V2X* [24], *V2XSet* contains more scenarios and considers imperfect real-world conditions. The benchmark supports 3D object detection and two test settings (perfect and noisy) for evaluation. *V2XSet* only contains one category object, the

TABLE II
A SUMMARY OF COLLABORATIVE PERCEPTION DATASETS.

Dataset	Year	Publication	Source	V2V	V2I	Viewpoints	RGB	Depth	Lidar	Link
T&J [41]	2019	ICDCS	Real-World	✓	-	2	-	-	✓	Link
V2V-Sim [19]	2020	ECCV	LiDARsim	✓	-	-	-	-	✓	-
CoopInf [51]	2020	TITS	CARLA	-	✓	-	✓	✓	-	Link
V2X-Sim [22]	2021	RAL	CARLA & SUMO	✓	✓	2-5	✓	✓	✓	Link
COOD [73]	2021	RAL	CARLA	✓	-	-	-	-	✓	Link
COMAP [98]	2022	RAL	CARLA & SUMO	✓	-	-	-	-	✓	Link
OPV2V [23]	2022	ICRA	CARLA & OpenCDA	✓	-	2-7	✓	-	✓	Link
AUTOCASTSIM [76]	2022	CVPR	CARLA	✓	-	-	✓	-	✓	Link
DAIR-V2X-C [24]	2022	CVPR	Real-World	-	✓	2	✓	-	✓	Link
V2XSet [21]	2022	ECCV	CARLA & OpenCDA	✓	✓	2-5	✓	-	✓	Link
DOLPHINS [99]	2022	ACCV	CARLA	✓	✓	3	✓	-	✓	Link

Viewpoints represents the number of collaboration agents.

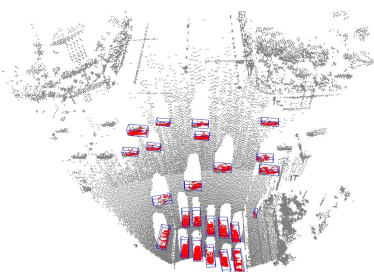


Fig. 6. 3D object detection [24]

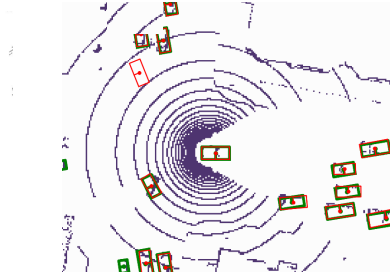


Fig. 7. BEV-based 3D object detection [22]



Fig. 8. BEV semantic segmentation [22]

same as OPV2V.

B. Evaluation on 3D Object Detection

1) *Problem Definition*: Object detection is one of the most fundamental and challenging problems in computer vision, the goal of which is to localize and recognize objects. According to the dimension of the scene, object detection can be divided into 2D object detection and 3D object detection. Collaborative object detection mainly focuses on 3D object detection. Given a single frame, 3D collaborative object detection models will predict 3D bounding boxes (see Fig.6) or BEV bounding boxes (see Fig.7) of the target objects.

2) *Evaluation Metrics*: Most object detection benchmarks adopt average precision (AP) [95, 96, 103] at a specific Intersection-over-Union (IoU) threshold as an evaluation metric, as does collaborative detection. Average precision (AP) is defined as the area under the continuous precision-recall (PR) curve, approximated through numeric integration over a finite number of sample points, and the mean average precision (mAP) is the average AP of each class, which reflects the accuracy of the detection prediction bounding boxes under a certain category. The detailed calculation process for 2D detection can be found in [103], which is also suitable for 3D object detection. Based on the format of model output, the

metrics for collaborative detection usually contain AP_{3D} and AP_{BEV} , which represent Average Precision (AP) at specific Intersection-over-Union (IoU) thresholds for 3D bounding boxes and 2D bird's eye view (BEV) maps respectively.

3) *Quantitative Results*: To evaluate mainstream collaboration approaches, we summarize qualitative results of object detection on four typical dataset benchmarks, and all results are collected from papers and official websites. Experiments in Tab.III and Tab.IV are in V2V mode, while Tab.V and Tab.VI are in V2X mode. We can find that mainstream collaboration methods utilize lidar points as input.

In the V2X-Sim BEV detection benchmark (Tab.III), early collaboration and late collaboration always become the upper-bound and lower-bound respectively. Although Who2com [71] and When2com [72] adopt attention mechanisms to select interacting agents and time, the simple fusion operation makes its performance worse than lower-bound. On the contrary, adaptive fusion strategy-based methods such as V2VNet [19], DiscoNet [20] and CRCNet [29] can achieve more ideal results than late collaboration.

Intermediate collaboration could surpass early collaboration in OPV2V (Tab.IV) and V2XSet (Tab.VI) 3D object detection benchmarks. In the OPV2V benchmark, V2VNet [19] and FPV-RCNN [53] perform well in their ingenious fusion

TABLE III
QUANTITATIVE RESULTS OF 3D OBJECT DETECTION ON V2X-SIM [22].

Method	Modality	Backbone	Scheme	$AP_{BEV}@0.5$	$AP_{BEV}@0.7$
Individual	Lidar	FaF [104]	No	45.8	40.6
Late Collab	Lidar	FaF [104]	Late	55.4	41.8
Early Collab	Lidar	FaF [104]	Early	64.2	60.3
Who2com [71]	Lidar	FaF [104]	Inter	47.2	42.2
When2com [72]	Lidar	FaF [104]	Inter	47.9	42.9
V2VNet [19]	Lidar	FaF [104]	Inter	57.0	49.1
DiscoNet [20]	Lidar	FaF [104]	Inter	60.2	53.7
CRCNet [29]	Lidar	FaF [104]	Inter	61.1	55.3

TABLE IV
QUANTITATIVE RESULTS OF 3D OBJECT DETECTION ON OPV2V [23].

Method	Modality	Backbone	Scheme	$AP_{3D}@0.7$	
				Default	Culver
Individual	Lidar	PointPillars [6]	No	60.2	47.1
Late Collab	Lidar	PointPillars [6]	Late	78.1	66.8
Early Collab	Lidar	PointPillars [6]	Early	80.0	69.6
F-Cooper [42]	Lidar	PointPillars [6]	Inter	79.0	72.8
V2VNet [19]	Lidar	PointPillars [6]	Inter	82.2	73.4
AttFusion [23]	Lidar	PointPillars [6]	Inter	81.5	73.5
FPV-RCNN [53]	Lidar	PointPillars [6]	Inter	82.0	76.3

strategy. However, in the V2XSet benchmark, V2VNet [19] and AttFusion [23] are weaker than F-Cooper [42], which adopts maxout to fuse features. The possible reason is that a homogeneous collaboration structure brings more noise to the heterogeneous scenario. Especially, V2X-ViT [21] achieves better performance for its specially designed framework for V2X heterogeneous collaboration.

In DAIR-V2X-C [24] datasets, only early and late collaboration results are provided. We can find both collaboration schemes could improve the performance of vehicles effectively. However, the performance of collaborative perception degrades in the asynchronous phenomenon, TCLF [24] can alleviate the impact of asynchrony to a certain extent.

C. Evaluation on BEV Semantic Segmentation

1) *Problem Definition*: BEV semantic segmentation aims to predict a rasterized map with surrounding semantics under the BEV view, as shown in Fig.8. Generally, models take lidar points and multi-cameras as input to conduct semantic segmentation. In the collaborative perception scene, multiple agents provide information in distinct views, facilitating semantic scene understanding.

2) *Evaluation Metrics*: The input of the model can be lidar or RGB cameras, and the output of the model is BEV semantic segmentation. To accomplish this task, collaborative perception datasets require labeling the semantic segmentation in given categories. The common performance metric for this task is Intersection over Union (IoU) between map prediction and ground truth map-view labels.

TABLE V
QUANTITATIVE RESULTS OF 3D OBJECT DETECTION ON DAIR-V2X-C [24].

Method	Modality	Backbone	Dataset	$AP_{3D}@0.5$	$AP_{BEV}@0.5$
Veh-Only	Image	ImvoxelNet [44]	VIC-Sync	12.03	13.62
Inf-Only	Image	ImvoxelNet [44]	VIC-Sync	19.93	25.31
Late Collab	Image	ImvoxelNet [44]	VIC-Sync	26.56	37.75
Veh-Only	Lidar	PointPillars [6]	VIC-Sync	31.33	35.06
Inf-Only	Lidar	PointPillars [6]	VIC-Sync	17.62	24.40
Late Collab	Lidar	PointPillars [6]	VIC-Sync	41.90	47.96
Early Collab	Lidar	PointPillars [6]	VIC-Sync	50.03	53.73
Late Collab	Lidar	PointPillars [6]	VIC-Async-1	40.21	46.61
Late Collab	Lidar	PointPillars [6]	VIC-Async-2	35.29	40.65
Early Collab	Lidar	PointPillars [6]	VIC-Async-1	47.47	51.67
TCLF [24]	Lidar	PointPillars [6]	VIC-Async-1	40.79	46.80
TCLF [24]	Lidar	PointPillars [6]	VIC-Async-2	36.72	41.67

¹ Veh and Inf stand for vehicle and infrastructure respectively.
² VIC-Sync and VIC-Async represent temporal synchronous and asynchronous phenomenon respectively.

TABLE VI
QUANTITATIVE RESULTS OF 3D OBJECT DETECTION ON V2XSET [21].

Method	Modality	Backbone	Scheme	$AP_{3D}@0.7$	
				Perfect	Noisy
Individual	Lidar	PointPillars [6]	No	40.2	40.2
Late Collab	Lidar	PointPillars [6]	Late	62.0	30.7
Early Collab	Lidar	PointPillars [6]	Early	71.0	38.4
F-Cooper [42]	Lidar	PointPillars [6]	Inter	68.0	46.9
AttFusion [23]	Lidar	PointPillars [6]	Inter	66.4	48.7
V2VNet [19]	Lidar	PointPillars [6]	Inter	67.7	49.3
DiscoNet [20]	Lidar	PointPillars [6]	Inter	69.5	54.1
V2X-ViT [21]	Lidar	PointPillars [6]	Inter	71.2	61.4

3) *Quantitative Results*: We list BEV semantic segmentation results in Tab.VII and Tab.VIII. We only select experiments in V2V mode, and the results demonstrate the effectiveness of collaboration on BEV semantic segmentation.

In the OPV2V dataset (Tab.VII), novel collaboration methods [19, 20, 42] on 3D object detection achieve good segmentation results, while their performance is not as good as CoBEVT [78], which is specially designed for multi-view multi-agent fusion. V2X-Sim benchmark (Tab.VIII) provides BEV segmentation on six categories. We can find that regularly shaped objects are easier to be identified, such as vehicles. Besides, V2VNet [19] and DiscoNet [20] are superior to early collaboration in terms of pedestrian, sidewalk and terrain. This shows that the rich semantic information extracted by each agent is more beneficial to the task.

VI. CHALLENGES AND OPPORTUNITIES

In recent years, collaborative perception in autonomous driving has made rapid progress, ranging from traditional strategies to more complex methods. However, there are some outstanding issues that must be addressed. We propose open

TABLE VII
QUANTITATIVE RESULTS OF BEV SEMANTIC SEGMENTATION ON OPV2V [23].

Method	Modality	Backbone	Vehicle	Terrain	Lane
Individual	Image	CVT [105]	37.7	57.8	43.7
Map Collaboration	Image	CVT [105]	45.1	60.0	44.1
F-Cooper [42]	Image	CVT [105]	52.5	60.4	46.5
AttFusion [23]	Image	CVT [105]	51.9	60.5	46.2
V2VNet [23]	Image	CVT [105]	53.5	60.2	47.5
DiscoNet [20]	Image	CVT [105]	52.9	60.7	45.8
FuseBEVT [78]	Image	CVT [105]	59.0	62.1	49.2
CoBEVT [78]	Image	SinBEVT [78]	60.4	63.0	53.0

¹ FuseBEVT only uses the multi-agent fusion module.

² CoBEVT uses both of multi-view fusion (SinBEVT) and multi-agent fusion (FuseBEVT) modules.

problems based on difficulties in collaborative perception and other real-world problems. In addition, we also provide some suggestions about the future development of collaborative perception in autonomous driving.

A. Transmission and Computing Efficiency

Transmission and computing efficiency is essential for multi-agent systems. Generally speaking, the total inference time of the collaboration framework contains transmission time and computing time. The limited bandwidth increases the transmission time and the aggregation of collaborative information occupies the computing time, which will dramatically influence real-time collaboration. Experiments have demonstrated the amount of data transmission determines the transfer time and the total runtime [42]. In order to reduce the latency and improve computing efficiency, feature compression and selection for transmitted data will be vital to collaborative perception.

Feature compression improves intermediate collaboration efficiency by minimizing transmitted data's latency and energy. Existing methods usually realize feature-map compression with classic compression policy [65, 107], which achieves a tradeoff between transmission bandwidth and accuracy. Since the compression methods are sourced from image compression, the performance of collaborative perception is affected marginally. Hence, a more suitable feature compression strategy should be considered (e.g. the technology of separate compression in the foreground and background).

Another aspect of enhancing computing efficiency is key information selection, however, only a few works [29, 52, 53, 76] have focused on the redundancy of the feature map. Future works are encouraged to follow two-stage [53] or one-stage [52] methods to calculate blind and weak perception areas of the ego vehicle and further select the required collaborative information to realize high computing efficiency.

B. Collaboration Perception in Complex Scenes

How to achieve robust and accurate perception performance under various complex and critical scenes is a key issue

in autonomous driving, which will also affect the efficiency of collaboration. Although a number of large-scale datasets have emerged in recent years, they are primarily designed for ordinary scenarios and failed to cover complex and challenging scenes (such as bad weather, highway and distant or small objects). In these scenes, sensors may be affected by light or distance to produce low-quality data, and there may be serious spatiotemporal inconsistencies between agents due to high-speed movement, all of which can lead to instability and uncertainty in collaborative perception systems.

In order to construct a more robust system, there is an urgent need to collect collaborative perception data in complex environments and propose well-designed methods for various complex scenarios. Multi-sensor fusion helps compensate for weather and distance's effects on data quality, and virtual point cloud generation [108, 109, 110] can be used to predict long-range objects. Additionally, spatio-temporal data fusion is required to predict the trajectory of objects moving at high speeds, and these are promising directions for future research.

C. Domain Adaption for Realistic Collaborative Perception

Large-scale datasets used to be a bottleneck in the collaborative perception of autonomous driving, but recent published datasets and benchmarks have significantly boosted this field. However, due to the difficulty of scene construction and data collection in reality, most collaborative perception datasets are generated from simulators. The real-world collection of datasets [24] only contains V2I scenarios, as shown in Tab.II. Realistic collaboration scenarios are more complex than ideal ones, such as weak signals, high density and harsh environments. Despite the success of collaborative perception on simulated datasets, the performance degrades quickly in the real scenes for domain gaps. In practical applications, visual models are required to work under simulated, constrained conditions and be able to perform stably in highly realistic scenes. Consequently, adapting to natural and unseen domains without specific guidance is essential for collaborative perception.

One way to achieve a robust collaborative perception model under realistic scenes is to rely on large-scale labeled real datasets. Unfortunately, it is tough to collect and annotate diverse V2V/V2I/V2X scenarios in the near future. In order to address this challenge, unsupervised domain adaption (UDA) [10, 111] is a feasible approach. UDA can transfer information from the source domain to the target domain. With the benefit of UDA, people can transfer collaborative perception models to the realistic domain and other simulated domains. This technology will aid in generating real large-scale datasets and applying collaborative perception.

VII. CONCLUSION

In this work, we present a survey on collaborative perception in autonomous driving. We begin by briefly introducing basic technologies and then summarize the collaboration scheme. Following that, a thorough examination of recent collaborative perception methods is presented. We specifically summarize the collaboration modules in perception networks in terms of how to improve collaboration efficiency and performance, as

TABLE VIII
QUALITATIVE RESULTS OF BEV SEMANTIC SEGMENTATION ON V2X-SIM [22].

Method	Modality	Backbone	Vehicle	Pedest	Build	Veget	Sidewalk	Terrain	Road	mIoU
Individual	Lidar	U-Net [106]	45.93	20.59	25.38	35.83	42.39	47.03	65.76	36.64
Late Collab	Lidar	U-Net [106]	47.67	10.78	25.26	39.46	48.79	50.92	70.00	38.38
Early Collab	Lidar	U-Net [106]	64.09	31.54	29.07	45.04	41.34	48.20	67.05	42.29
Who2com [71]	Lidar	U-Net [106]	47.74	19.16	26.11	39.64	33.60	35.81	56.75	33.81
When2com [72]	Lidar	U-Net [106]	47.74	19.16	26.11	39.64	33.60	35.81	56.75	33.81
V2VNet [19]	Lidar	U-Net [106]	58.42	21.99	28.58	41.42	48.33	48.51	70.02	41.11
DiscoNet [20]	Lidar	U-Net [106]	56.98	22.02	27.36	42.50	46.98	50.22	68.62	40.84

well as how to ensure collaboration robustness and safety. There are also large-scale collaborative perception datasets and performance comparisons on these benchmarks. Finally, we propose new perspectives with respect to the practical implementation issues of collaborative perception applications.

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