

FocalComm: Hard Instance-Aware Multi-Agent Perception

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Abstract

*Multi-agent collaborative perception (CP) is a promising paradigm for improving autonomous driving safety, particularly for vulnerable road users like pedestrians, via robust 3D perception. However, existing CP approaches often optimize for vehicle detection performance metrics, underperforming on smaller, safety-critical objects such as pedestrians, where detection failures can be catastrophic. Furthermore, previous CP methods rely on full feature exchange rather than communicating only salient features that help reduce false negatives. To this end, we present **FocalComm**, a novel collaborative perception framework that focuses on exchanging hard-instance-oriented features among connected collaborative agents. FocalComm consists of two key novel designs, (1) a learnable progressive hard instance mining (HIM) module to extract hard instances-oriented features per agent, and (2) a query-based feature-level (intermediate) fusion technique that dynamically weights these identified features during collaboration. We show that FocalComm outperforms state-of-the-art collaborative perception methods on two challenging real world datasets (V2X-Real and DAIR-V2X) across both vehicle-centric and infrastructure-centric collaborative setups. FocalComm also shows strong performance gain in pedestrian detection in V2X-Real. Code and model checkpoints are available at <https://github.com/scdrand23/FocalComm>.*

1. Introduction

The ability to perceive and interpret the surroundings accurately is at the core of the promise of autonomous vehicle (AV) systems. Research in AVs [2, 10, 28] has made significant progress, with the potential for a future of safer and more efficient intelligent transportation systems. At the core of this progress lies robust perception. While single-vehicle perception has advanced significantly through multi-sensor fusion (cameras, LiDAR, radar) and data intensive learning-based techniques, it remains constrained by limited field-of-view, occlusions, and degraded performance at long ranges.

Multi-agent¹ CP where vehicles and infrastructure share complementary perception data through V2X communication has shown promise to address this. CP enables connected autonomous vehicles (CAVs) and infrastructure units to exchange visual perception information and scene representations from multiple viewpoints, mitigating single-agent perception limitations and improving detection reliability for safety-critical scenarios.

Collaboration can be at raw level (early fusion), feature level (intermediate fusion), or decision level (late fusion), based on the data sharing stage [11]. Early fusion exchanges unprocessed sensor data (images, LiDAR point clouds), requiring high communication bandwidth but enabling comprehensive joint processing. Late fusion transmits only final detection outputs (e.g., bounding boxes), minimizing bandwidth needs but potentially introducing delays and information loss. Intermediate fusion strikes a balance by sharing compressed feature representations, offering a practical compromise between communication efficiency and perception performance. Current research has explored various aspects of CP, including bandwidth optimization and selective information transmission. Works such as Where2comm [12] have focused on optimizing bandwidth usage by selectively transmitting informative features, while others like V2X-ViT [35] have addressed challenges such as noisy localization. Recent advances like SyncNet [17] have made progress in latency-aware collaboration, while MPDA [34] and DI-V2X [33] have tackled domain gap in multi-agent collaboration.

The detection of vulnerable road users such as pedestrians remains understudied in CP settings, both in terms of available datasets and methodological approaches. While current CP systems achieve good performance on vehicle detection, they significantly underperform on pedestrian detection. This performance gap is of much concern as pedestrian detection poses unique challenges due to their smaller size, occlusions, and weak sensing from long ranges, yet they represent critical safety risks when missed (nearly

¹An agent refers to either a vehicle or infrastructure unit with both perception capability (e.g. LiDAR) and V2X communication modules that enable it to share and receive information.

7,522 pedestrian deaths in the USA in 2022 alone [22]). Therefore, there is a pressing need for CP systems that can effectively handle multi-class detection scenarios, particularly for safety-critical classes like pedestrians.

To address this challenge, we draw inspiration from a well-established line of work in single-agent perception: hard instance mining. These techniques, which identify and prioritize difficult-to-detect objects through loss-based sampling [26] or adaptive weighting [6, 19, 31], have shown significant promise. They have proven particularly effective at improving detection performance on challenging objects by giving more focus on the most difficult examples during training, with recent works like FocalFormer3D [6] and HINTED [31] demonstrating strong results on general 3D detection tasks. These approaches have led to improvements in detecting difficult instances such as small objects, partially occluded targets, and objects at long range. Motivated by these advances, we observe that hard instance focused collaboration could significantly benefit multi-agent perception by addressing communication constraints and detection challenges simultaneously. Adapting these techniques to CP requires careful architectural design to effectively prioritize difficult instances across multiple agents with bandwidth constraints.

In this paper, we introduce FocalComm, a novel multi-agent CP method that prioritizes hard instance-oriented features based on a learnable difficulty-aware instance identification approach. Our approach consists of a stage-wise hard instance identification module followed by adaptive feature fusion module that selectively combines information from multiple agents based on instance-level difficulty queries. Our approach is motivated by the observation that not all objects require equal collaborative effort. While vehicles are often detected reliably by a single agent, pedestrians and smaller objects benefit more from multi-agent collaboration due to their size and likelihood of occlusion. By focusing exchanging information about these challenging instances, FocalComm achieves superior performance on the real multi-class multi-agent collaborative perception benchmark [32]. Our contributions in this paper can be summarized as follows.

1. We develop a multi-stage hard instance mining technique that extracts features ranked with detection uncertainty across multiple object classes from each agent to progressively focus on increasingly difficult detection cases.
2. We propose a query-guided multi-agent feature aggregation strategy that prioritizes hard instance-oriented queries across collaborative agents while dynamically weighting of features and queries from each agent.
3. We present FocalComm, an end-to-end framework that integrates difficulty-aware mining and query-guided

fusion to achieve efficient CP, with particular benefits for hard-to-detect objects like pedestrians.

2. Related Work

Collaborative Perception Collaborative perception (CP) via vehicle-to-everything (V2X) communications presents a promising approach to enhance autonomous vehicles' ability to perceive through occlusions and extend long-range detection capabilities [35]. V2VNet [30] presents an intermediate-level fusion approach where vehicles compress and exchange intermediate network representations through a graph neural network. DiscoNet [18] implements a knowledge distillation-based fusion method, while AttFuse [36] develops an attention-based V2V framework and introduced the OPV2V benchmark. Addressing communication constraints is crucial for practical deployment of CP systems [25]. V2X-ViT [35] introduced vision transformer-based collaboration robust to noisy localization, while [17] addressed latency-aware collaboration through temporal alignment. Bandwidth optimization has been explored via spatial confidence maps [12], codebook compression [13], multi-resolution fusion [29], pragmatic communication [38], and vector quantization [24]. Recent works address heterogeneous agent collaboration [20,33,34], robustness to pose errors [21], sim2real adaptation [16], end-to-end driving [7], and unsupervised learning [5]. Further advances include latency-aware alignment [27], sparse fusion [41], and multi-modal datasets with 4D Radar [39].

Hard Instance-Aware Detection Detecting challenging objects accurately is crucial for reliable perception systems, particularly in safety-critical applications like autonomous driving. Early approaches to hard example mining include Online Hard Example Mining (OHEM) [26], which dynamically selects the most difficult examples during training by computing losses for all region proposals and selecting those with highest losses, while using non-maximum suppression to prevent redundant regions from dominating. Focal loss [19] takes a different approach by automatically down-weighting easy examples through a modified cross-entropy loss, addressing the extreme foreground-background class imbalance. More recent methods have explored specialized techniques for identifying and handling difficult samples. IoU-aware sampling [23] balances easy and hard examples based on their intersection over union (IoU) distributions, while Cascade R-CNN [3] employs a sequence of detectors with increasing IoU thresholds to progressively handle more difficult instances. In the 3D detection domain, researchers have developed various strategies to address challenging detection scenarios. SST [8] leverages attention mechanisms that preserve spatial information for small objects, while FSD [9] focuses on identifying objects in sparse, long-range contexts. Recent ad-

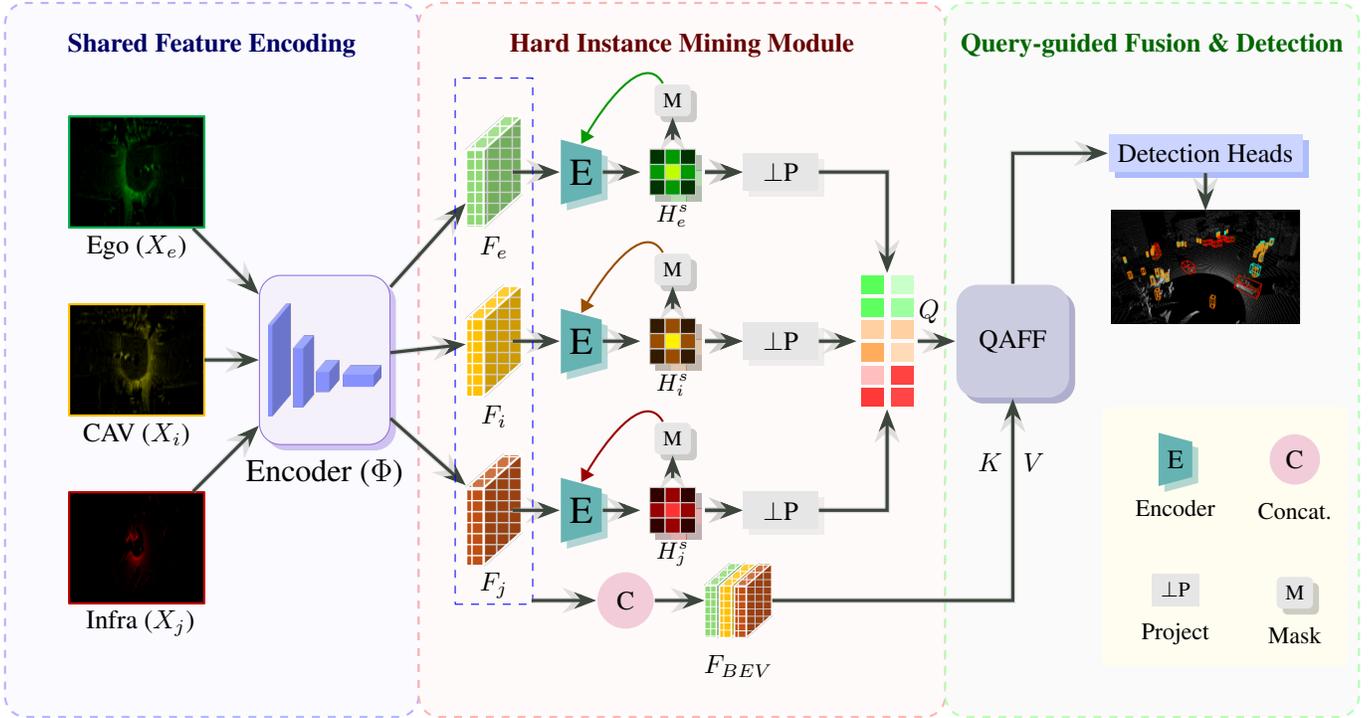


Figure 1. The overall architecture of FocalComm with three key components: (1) parallel feature extraction through a sparse 3D backbone network and encoding via voxel feature encoder (Φ), (2) progressive Hard Instance Mining (HIM) for feature-level identification of hard to detect objects across stages, and (3) Query-guided Adaptive Feature Fusion (QAFF) for aggregating multi-agent features based on instance-level queries.

vances have specifically targeted hard instance mining for 3D detection. FocalFormer3D [6] introduces a multi-stage Hard Instance Probing (HIP) mechanism that identifies potential false negatives through progressive refinement by maintaining class-aware accumulated positive masks to focus training on increasingly difficult instances while omitting easy positives. HINTED [31] addresses hard instances in sparsely-supervised settings by combining mixed-density feature fusion. Most recently, BEVFusion-DHIP [14] extends hard instance mining to multi-modal fusion by applying dual HIP to both LiDAR BEV features and 3D position-aware image features, systematically reducing false negatives crucial for autonomous driving safety. Despite these advances in single-agent perception, hard instance mining in collaborative perception scenarios remains largely unexplored. Our work, **FocalComm**, addresses this gap by developing a progressive hard instance mining technique tailored specifically for multi-agent CP scenarios, where challenging objects can be better identified and handled through collaborative information exchange.

3. FocalComm Framework

Our proposed FocalComm architecture is illustrated in Fig. 1. FocalComm processes inputs from multiple agents

including the ego vehicle, other connected autonomous vehicles (CAVs), and infrastructure sensors. Each agent’s point cloud data (X_e for ego, X_i for the other CAVs, and X_j for infrastructure) is first processed through identical sparse voxel feature encoders (denoted as Φ), producing agent-specific feature maps (F_e, F_i, F_j). These features are then processed through two key components: (1) a progressive Hard Instance Mining (HIM) module that generates stage-wise heatmaps (H_e^s, H_i^s, H_j^s) and suppresses easy samples using mask (\mathcal{M}) to focus on more challenging objects across multiple stages, and (2) Query-guided Adaptive Feature Fusion (QAFF) that aggregates the instance-aware queries from all agents into a unified representation, which is combined with concatenated BEV features (F_{BEV}) before feeding into the detection head.

Feature Extraction Each agent processes its point cloud data through a shared sparse voxel feature encoder Φ , producing agent-specific feature maps:

$$F_k = \Phi(X_k) \in \mathbb{R}^{H \times W \times C}, \quad k \in \{e, i, j\} \quad (1)$$

where X_k represents point cloud inputs from ego, CAV, and infrastructure agents.

Algorithm 1 Hard Instance Mining (HIM)

Require: Multi-agent features \mathcal{F} , GT boxes \mathcal{G} , stages S

- 1: $\mathcal{F}_{orig} \leftarrow \mathcal{F}$ \triangleright Cache
- 2: $\mathcal{M}_{acc} \leftarrow \mathbf{0}$ \triangleright Initialize
- 3: **for** $s \in \{1, \dots, n_S\}$ **do**
- 4: $\mathcal{M}_{spatial} \leftarrow \max(\mathcal{M}_{acc})$ \triangleright Flatten
- 5: $\mathcal{F}_{masked} \leftarrow \mathcal{F}_{orig} \odot (1 - \mathcal{M}_{spatial})$ \triangleright Mask
- 6: $\hat{\mathcal{F}}_s \leftarrow \Psi_s(\mathcal{F}_{masked})$ \triangleright Extract
- 7: $\mathcal{P}_s \leftarrow \Omega(\hat{\mathcal{F}}_s)$ \triangleright Detect
- 8: **if** training **then**
- 9: $\mathcal{T}_s \leftarrow \text{Match}(\mathcal{P}_s, \mathcal{G})$ \triangleright Assign
- 10: **else**
- 11: $\mathcal{T}_s \leftarrow \text{Filter}(\mathcal{P}_s)$ \triangleright Threshold
- 12: **end if**
- 13: $\mathcal{M}_{acc} \leftarrow \max(\mathcal{M}_{acc}, \mathcal{T}_s)$ \triangleright Update
- 14: **end for**
- 15: $\mathcal{Q} \leftarrow \text{Combine}(\{\hat{\mathcal{F}}_s\})$ \triangleright Fuse

Ensure: Query features \mathcal{Q} , Predictions $\{\mathcal{P}_s\}$, Masks $\{\mathcal{T}_s\}$

3.0.1 Hard Instance Mining (HIM)

A key part of FocalComm is the Hard Instance Mining (HIM) module that extracts hard instance identifying features in a multi-stage manner. Each stage focuses on increasingly difficult instances while avoiding redundant attention to already-identified objects through mask accumulation. As detailed in Algorithm 1, HIM processes features through n_S progressive stages. The key innovation lies in the progressive masking: at each stage s , the accumulated mask \mathcal{M}_{acc} suppresses detected regions through $\mathcal{F}_{masked} = \mathcal{F}_{orig} \odot (1 - \mathcal{M}_{spatial})$, forcing subsequent stages to focus on harder instances. The Match() and Filter() functions handle mask generation differently for training and inference. During training, Match($\mathcal{P}_s, \mathcal{G}$) performs Hungarian assignment between predictions and ground truth, returning binary masks at locations where IoU exceeds τ_{iou} . During inference, Filter(\mathcal{P}_s) applies confidence thresholding: $\mathcal{T}_s = \mathbf{1}[\sigma(H_s) > \tau \cdot \gamma^s]$, where H_s is the dense heatmap, τ is the base threshold, and γ is a decay factor controlling stage-wise threshold progression. Each stage produces features $\hat{\mathcal{F}}_s$ concatenated to form query features $\mathcal{Q} \in \mathbb{R}^{N \times (n_S \cdot C) \times H \times W}$.

3.0.2 Query-guided Adaptive Feature Fusion (QAFF)

The Query-guided Adaptive Feature Fusion (QAFF) module takes instance-aware queries from HIM to aggregate information across multiple agents. As shown in Algorithm 2, QAFF takes as input the stage-wise query features $\{\mathcal{Q}_s^i\}_{s=1}^S$ from each agent i , along with their original features $\mathcal{F}_i \in \mathbb{R}^{C \times H \times W}$ and a valid agent mask $\mathbf{M} \in \{0, 1\}^N$ indicating participating agents in the scene. For stage

Algorithm 2 Query-guided Adaptive Feature Fusion (QAFF)

Require: Query features $\{\mathcal{Q}_s^i\}_{s=1}^{n_S}$ from each agent i , Agent features $\mathcal{F}_i \in \mathbb{R}^{C \times H \times W}$, Valid agent mask $\mathbf{M} \in \{0, 1\}^N$

- 1: **for** $s \in \{1, \dots, n_S\}$ **do**
- 2: $\tilde{\mathcal{Q}}_s \leftarrow \text{MHSA}(\{\mathcal{Q}_s^i\}_i, \mathbf{M})$ \triangleright Cross-agent attention
- 3: **end for**
- 4: $\omega_s \leftarrow \text{softmax}(\text{SA}(\tilde{\mathcal{Q}}_s))$ \triangleright Stage importance weights
- 5: $\bar{\mathcal{Q}} \leftarrow \sum_{s=1}^S \omega_s \tilde{\mathcal{Q}}_s$ \triangleright Stage-wise feature aggregation
- 6: $\mathbf{K}, \mathbf{V} \leftarrow \text{Proj}(\{\mathcal{F}_i\}_i)$ \triangleright Project features to key-value
- 7: $\mathcal{F}_{cross} \leftarrow \text{MHCA}(\bar{\mathcal{Q}}, \mathbf{K}, \mathbf{V}, \mathbf{M})$ \triangleright Query-guidance
- 8: $\alpha_i \leftarrow \text{softmax}(\text{AA}(\mathcal{F}_{cross}) \odot \mathbf{M})$ \triangleright Agent weights
- 9: $\mathcal{F}_{out} \leftarrow \sum_i \alpha_i \mathcal{F}_{cross}^i$ \triangleright Weighted feature fusion

Ensure: Fused features $\mathcal{F}_{out} \in \mathbb{R}^{C \times H \times W}$

s , QAFF first performs multi-head self-attention (MHSA) across agents to generate stage-specific representations $\tilde{\mathcal{Q}}_s$. This cross-agent attention mechanism allows agents to collaboratively refine their understanding of objects at each difficulty level while accounting for potentially missing or inactive agents through the mask \mathbf{M} . The stage-wise representations are then combined through learned importance weights ω_s , computed via a stage attention (SA) mechanism and softmax normalization. This adaptive weighting scheme produces a unified query representation $\bar{\mathcal{Q}} = \sum_{s=1}^S \omega_s \tilde{\mathcal{Q}}_s$ that emphasizes the most informative stages based on the current scene context. The original agent features $\{\mathcal{F}_i\}_i$ are projected into key-value space to obtain \mathbf{K} and \mathbf{V} . Multi-head cross-attention (MHCA) is then applied between the unified queries $\bar{\mathcal{Q}}$ and these key-value pairs, producing \mathcal{F}_{cross} that captures comprehensive multi-agent understanding. Finally, agent-specific attention weights α_i are computed through an agent attention (AA) mechanism, taking into account the valid agent mask \mathbf{M} . These weights determine each agent's contribution to the final fused output $\mathcal{F}_{out} = \sum_i \alpha_i \mathcal{F}_{cross}^i$, emphasizing agents with more informative observations. These weights automatically emphasize agents with more reliable or informative observations, accounting for variations in viewpoint quality and sensing capabilities. The output of QAFF is then passed to the detection decoders (shown in purple in Fig. 1) for final object detection and classification.

3.1. Detection Decoder and Joint Optimization

The final fused features, F_{Fuse} , are passed to the detection head. Different from previous multi-agent collaborative perception works, we adopt an anchor-free detection head [1] that supervises the regression and classification tasks as well as allows joint optimization of the multistage hard instance identification. This anchor-free ap-

proach eliminates the need for complex predefined anchor designs and provides more direct object localization, which is particularly beneficial for detecting hard instances with unusual scales or occlusion patterns that traditional anchor-based methods might struggle with. Furthermore, our approach naturally handles multi-class detection scenarios, effectively identifying various road users including pedestrians, which exhibit significant variation in size and appearance. Our detection head consists of a transformer decoder based on [1] that processes feature queries from a dense heatmap prediction branch. The detection tasks are jointly optimized with hierarchical instance mining through a multi-component loss function:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{cls} + \lambda_2 \mathcal{L}_{bbox} + \lambda_3 \mathcal{L}_{hm} + \lambda_4 \sum_{s=1}^S \mathcal{L}_{him}^s \quad (2)$$

where \mathcal{L}_{cls} is the focal classification loss, \mathcal{L}_{bbox} is the L1 regression loss for bounding box parameters, \mathcal{L}_{hm} is the Gaussian focal loss for heatmap prediction. \mathcal{L}_{him}^s represents the progressive loss for the multi-stage hard instance mining at stage s . The weights λ_1 , λ_2 , λ_3 , and λ_4 balance the contributions of different loss components. The specific values of these hyperparameters are provided in the implementation details section.

4. Experiments

We evaluate **FocalComm** on V2XReal [32] and DAIR-V2X [40] datasets. To the best of our knowledge, V2X-Real is the only publicly accessible multi-agent collaborative real dataset with enough multiclass annotation including pedestrians. For training, we randomly assign one agent as the ego vehicle, while at inference time we use predefined ego agents based on the dataset’s categorization. Our experiments evaluate performance under two configurations, *i.e.* vehicle-centric and infrastructure-centric, where the ego agent is vehicle and infrastructure, respectively. For a fair comparison, all methods are implemented using the same 3D backbone [37] and anchor-free head [1]. We adopt a voxel-based method and anchor-free detection head across all compared models to push for improved detection performance for smaller classes such as pedestrians while ensuring fair comparison in collaborative perception.

4.1. Datasets

V2X-Real. V2X-Real [32] is a large-scale real-world dataset designed for V2X cooperative perception. It includes 33K LiDAR frames and over 1.2 million annotated 3D bounding boxes. The dataset is collected using two connected automated vehicles and two smart infrastructures. The dataset is collected in two scenarios: V2X smart intersections and V2V corridors. There are a maximum of four agents in a scene. The V2X-Real dataset contains

multi-class (vehicle, pedestrian, and truck) annotation and it allows vehicle-centric and infrastructure-centric CP evaluation. We use the train/val/test split with 23379, 2770, and 6850 frames respectively as proposed in the benchmark [32].

DAIR-V2X DAIR-V2X [40] is the first large-scale real-world dataset for Vehicle-Infrastructure cooperative perception. The dataset comprises 71K LiDAR and camera frames collected from real scenarios with comprehensive 3D annotations. It features vehicle-infrastructure collaboration with temporal asynchrony challenges and includes V2X-Seq extension with 15K frames for sequential perception and trajectory forecasting tasks.

Implementation Details. During training, we voxelize the point cloud with a voxel size of $0.2m \times 0.2m \times 0.4m$ and use a range of $[-100m, 100m]$ for the x and y axes, and $[-10m, 6m]$ for the z axis. Each voxel aggregates up to 20 points. We implement FocalComm using PyTorch and train on four H100 GPUs with a batch size of 8 for 50 epochs with Adam [15] optimizer with learning rate starting at $1e^{-4}$ and applying a weight decay of $1e^{-2}$. Our model employs a standard sparse 3D CNN backbone commonly used in LiDAR-based 3D detection, similar to VoxelNet [43] and SECOND [37]. The progressive hard instance mining (HIM) module employs a multi-stage architecture with confidence thresholds of 0.4, utilizing a pooling kernel size of 3 for local detection peaks and masking with an attention decay factor of 2.0 to progressively identify challenging instances. Our query-guided adaptive feature fusion (QAFF) module employs multi-head attention with 8 heads and hidden dimension of 256 to dynamically fuse features across agents based on query importance. The detection head follows a TransFusion [1] head with separate prediction branches for center, height, dimension, and rotation. Our multi-component loss function balances detection and mining objectives with weights $\lambda_1 = 1.0$ for classification, $\lambda_2 = 2.0$ for bounding box regression, $\lambda_3 = 1.0$ for heatmap prediction, and $\lambda_4 = 0.5$ for the hard instance mining component per agent. These weights were determined through extensive ablation studies on the validation set. The weights λ_1 - λ_3 follow established practices in prior detection works [1], while λ_4 was specifically tuned for our approach to prevent overfitting to difficult examples early in training while still ensuring sufficient gradient flow for learning challenging cases. This balance ensures stable convergence while maintaining focus on both common and rare detection scenarios.

4.2. Quantitative Evaluation

Evaluation Protocol. Similar to the evaluation protocol in V2VNet [30] and V2X-Real [32], our evaluation is done

Method	V2XReal ($K_{max} = 4$)								DAIR-V2X ($K_{max} = 2$)	
	Car		Pedestrian		Truck		Overall		Vehicle	
	VC	IC	VC	IC	VC	IC	VC	IC	VC	
	AP@0.3/0.5	AP@0.3/0.5	AP@0.3/0.5	AP@0.3/0.5	AP@0.3/0.5	AP@0.3/0.5	mAP@0.3/0.5	mAP@0.3/0.5	AP@0.3	AP@0.5
No Collaboration	73.7/68.4	70.6/59.1	31.8/13.9	29.7/10.7	21.2/15.7	46.6/42.0	42.2/32.7	49.0/37.3	58.9	54.4
F-Cooper [4]	88.3/85.6	84.3/80.8	47.8/22.7	45.4/15.9	47.9/46.1	48.3/47.9	61.3/51.4	59.4/48.2	70.4	64.8
V2VNet [30]	87.0/84.4	85.0/81.4	34.5/13.9	36.5/15.2	40.0/36.8	44.3/41.9	53.8/45.0	55.3/46.2	69.5	63.5
Attfuse [34]	81.3/80.7	81.5/80.9	46.8/21.7	48.5/24.8	49.6/47.7	47.6/45.7	59.2/50.0	59.2/50.5	69.7	63.8
CoBEVT [12]	87.2/85.6	84.1/82.1	54.8/26.1	52.3/25.6	50.1/45.1	48.9/47.8	64.0/53.3	61.7/52.9	72.8	65.7
V2XViT [35]	83.9/81.1	81.4/78.2	38.5/15.2	33.5/13.3	42.5/35.6	45.4/38.9	55.0/44.0	53.4/43.5	74.5	67.6
CoAlign [21]	85.8/83.4	84.7/83.4	38.3/17.3	36.4/14.8	52.7/43.9	53.2/51.1	59.9/48.2	58.1/49.8	76.9	69.7
ERMVP [42]	88.5/86.4	86.7/84.0	53.2/25.4	50.6/23.5	42.9/41.3	41.7/38.7	61.5/51.0	59.7/48.7	69.2	63.4
FocalComm (ours)	91.5/89.6	86.2/ 84.8	57.4/27.3	51.2/ 26.7	53.9/51.6	49.6/47.3	67.6/56.1	62.3/52.9	77.2	70.1

Table 1. Performance comparison on V2X-Real dataset under Vehicle-Centric (VC) and Infrastructure-Centric (IC) collaborative setups. Results show AP@0.3/AP@0.5 format. Best results are in boldface. In no collaboration mode, VC means vehicle only and IC means infrastructure only. K_{max} is the maximum number of agents per scene.

in the range of $[-100m, 100m]$ in both the x -axis and y -axis of the chosen ego agent. We adopt the standard average precision (AP) at intersection-over-union (IoU) threshold of 0.3 and 0.5 for each class and mean average precision averaged overall number of classes. Following established practices for datasets in V2X-Real with significant object size variations, we use these lower IoU thresholds to account for the challenging nature of detecting objects ranging from small pedestrians to large vehicles in CP scenarios.

Performance Comparison. Table 1 presents the comparison between our FocalComm and existing methods on the V2X-Real [32] dataset under both infrastructure-centric (IC) and vehicle-centric (VC) settings. Our method achieves state-of-the-art performance across all metrics, with significant improvements. In the vehicle-centric setting, FocalComm achieves 67.6% mAP@0.3 and 56.1% mAP@0.5, representing a 5.6% and 5.1% absolute improvement over the next best method (CoBEVT). The performance gains are particularly pronounced for pedestrian detection, where FocalComm achieves 57.4% AP@0.3 and 27.3% AP@0.5 in the vehicle-centric setting, significantly outperforming all baselines and addressing a critical safety need. Similarly, truck detection improves substantially from 21.2% to 53.9% AP@0.3, demonstrating our method’s effectiveness on challenging large objects. For infrastructure-centric scenarios, our method maintains strong performance with 62.3% mAP@0.3 and 52.9% mAP@0.5. On the DAIR-V2X dataset for vehicle detection, FocalComm achieves competitive results with 77.2% AP@0.3 and 70.1% AP@0.5, demonstrating strong generalization across different V2X scenarios.

Table 2 further validates our approach in specific communication scenarios. In V2V settings, FocalComm reaches 64.8% mAP@0.3, while in I2I configurations it achieves an impressive 70.2% mAP@0.3 and 58.1% mAP@0.5, outperforming all baselines by substantial margins. Analyzing per-class patterns, I2I consistently out-

performs V2V: truck detection benefits most (+10.3% AP@0.3, from 50.5% to 60.8%) due to infrastructure’s elevated viewpoint providing better coverage of large objects, while pedestrian detection gains +4.6% (53.9% to 58.5%) from reduced occlusions. Vehicle detection shows a smaller gap (+1.3%) as cars are well-detected from either perspective. These results demonstrate our method’s ability to effectively leverage the complementary viewpoints available in different collaboration scenarios.

4.3. Qualitative Evaluation

Detection Results. We visualize detection results from both infrastructure-centric (IC) and vehicle-centric (VC) perspectives across two scenes in Figure 2. Scene 1 (left) and Scene 2 (right) demonstrates our method’s performance at a complex intersection from bird’s-eye view. In Scene 1’s dense intersection, FocalComm accurately detects crowded pedestrians and most of the trucks, where previous methods often struggle with occlusions and object overlap. Scene 2 highlights our method’s effectiveness in detecting distant objects and multiple object classes. Through effective multi-agent collaboration, our method successfully detects cars (shown in red), pedestrians (shown in orange), and trucks (shown in magenta) across varying distances. The method particularly excels at maintaining reliable detection performance for distant objects and handling cases where objects are only partially visible. Our method achieves high precision with very few false positives, while maintaining high recall with minimal false negatives, as evidenced by the close alignment between predicted boxes and ground truth annotations across both scenes.

Query Features. To provide insights into our model’s attention mechanism, we visualize the mean of query features and their progression across the three stages of Hard Instance Mining (HIM) in Figure 3. The visualization shows results from two different agents, with each row representing an agent’s perspective. The first three columns show the

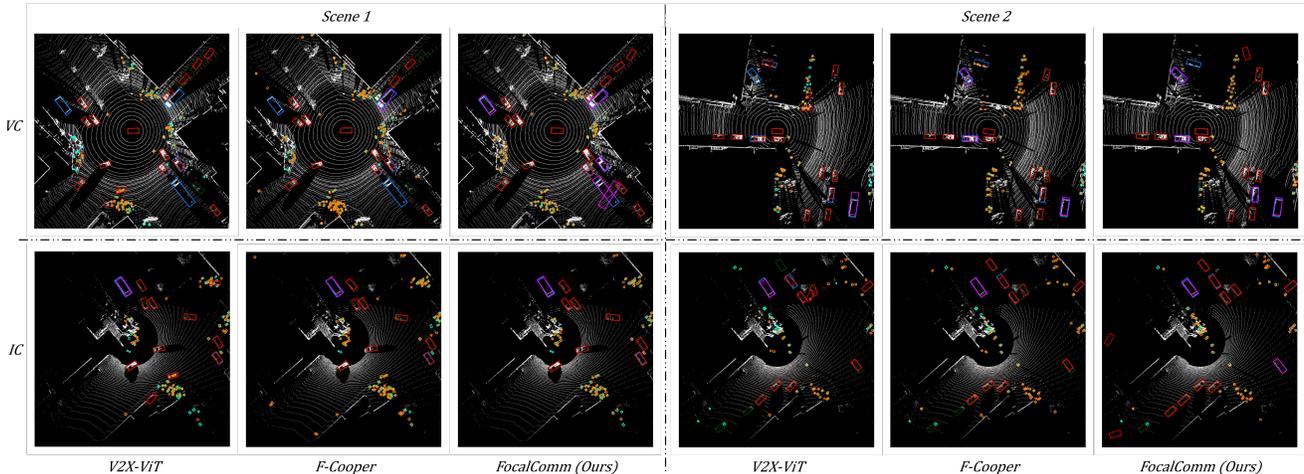


Figure 2. Qualitative detection results of FocalComm, V2XViT [35], and F-Cooper [4] on V2X-Real (cropped to 80×80 m around ego). Ground truth and predictions are shown for Car (GT: dark green, Pred: red), Pedestrian (GT: cyan, Pred: orange), and Truck (GT: light blue, Pred: magenta).

Method	V2X-Real Communication Scenarios							
	Vehicle		Pedestrian		Truck		Overall	
	V2V	I2I	V2V	I2I	V2V	I2I	V2V	I2I
	AP@0.3/0.5	AP@0.3/0.5	AP@0.3/0.5	AP@0.3/0.5	AP@0.3/0.5	AP@0.3/0.5	mAP@0.3/0.5	mAP@0.3/0.5
No Collaboration	73.7/68.4	70.6/59.1	31.8/13.9	29.7/10.7	21.2/15.7	46.6/42.0	42.2/32.7	49.0/37.3
F-Cooper [4]	86.6/83.2	84.0/79.9	45.3/23.3	49.7/21.0	45.5/40.8	59.3/58.2	59.1/49.1	64.3/53.0
V2VNet [30]	86.5/82.5	86.7/82.1	31.1/13.1	41.9/18.9	39.2/32.9	53.5/49.8	52.3/42.8	60.7/50.3
AttFuse [34]	81.1/79.9	82.8/81.8	44.4/20.5	52.1/28.2	48.7/46.5	57.4/55.3	58.1/49.0	64.1/55.1
CoBEVT [12]	86.1/83.9	84.0/81.1	51.0/28.5	53.1/30.6	48.6/43.3	61.9/60.1	61.9/51.9	66.3/57.2
V2X-ViT [35]	84.1/80.6	84.5/80.2	38.2/15.6	38.7/15.7	41.4/37.0	54.6/53.4	54.5/44.4	59.3/49.7
CoAlign [21]	83.6/80.8	83.5/82.0	37.4/17.1	41.1/17.4	50.1/36.1	57.0/54.4	57.0/44.7	60.5/51.3
ERMVP [42]	86.7/84.0	84.7/82.0	50.6/23.5	52.2/27.2	41.7/38.7	55.7/55.0	59.7/48.7	64.2/54.7
FocalComm (ours)	90.0/87.0	91.3/87.5	53.9/27.1	58.5/29.5	50.5/42.3	60.8/57.4	64.8/52.1	70.2/58.1

Table 2. Performance comparison on V2X-Real dataset for Vehicle-to-Vehicle (V2V) and Infrastructure-to-Infrastructure (I2I) communication scenarios. Results show AP@0.3/AP@0.5 format. For FocalComm, I2I corresponds to our normal collaborative setup. Best results are in boldface.

evolution of instance detection across stages, using color coding to distinguish between cars (green), pedestrians (magenta), and trucks (blue). We observe that Stage 1 captures a broader set of potential instances, while Stages 2 and 3 progressively refine and focus on previously undetected cases. The fourth column displays the generated query features as heatmaps along detection output, where brighter regions indicate higher weights.

4.4. Ablation Study

Core Component Analysis. To validate the effectiveness of our key components, we conduct ablation studies showing the incremental contribution of each module. As shown in Table 3, starting from a no-collaboration baseline with 42.2% overall AP@0.3, basic collaborative fusion (F-Cooper) improves performance to 61.3% (+19.1% absolute). Adding HIM alone to collaboration yields 66.2% AP@0.3 (+4.9% over baseline collaboration), while adding

QAFF alone achieves 65.5% AP@0.3 (+4.2% over baseline). The full model combining both HIM and QAFF reaches 67.6% AP@0.3, demonstrating synergy between the components with an additional 1.4-2.1% gain over individual components. The improvements are particularly notable for pedestrian detection (from 31.8% to 57.4% AP@0.3) and truck detection (from 21.2% to 53.9%), validating our focus on hard instance mining for challenging objects.

Compression Analysis. To evaluate the communication efficiency of FocalComm, we analyze the trade-off between detection performance and feature compression ratios. Figure 4 shows how our method’s performance varies across different compression levels from 1x (no compression) to 64x compression. We observe that FocalComm maintains robust performance up to 8x compression, with only a 2.5% drop in AP@0.3 (from 67.6% to 65.9%) and minimal degra-

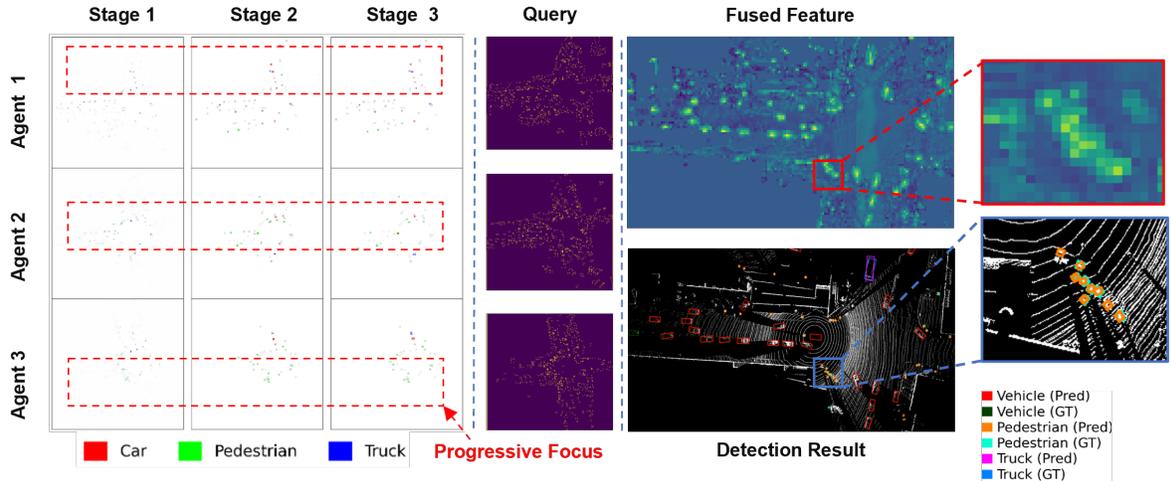


Figure 3. Visualization of our multi-stage Hard Instance Mining (HIM) process and query feature generation. The figure shows results from two agents (rows) across three HIM stages (first three columns), with detections color-coded as Car (green), Pedestrian (magenta), and Truck (blue). The fourth column shows query feature heatmaps where brighter colors indicate higher attention weights. The rightmost column provides detection results. This progression demonstrates how our model systematically refines detection focus across stages in a multi-agent setup.

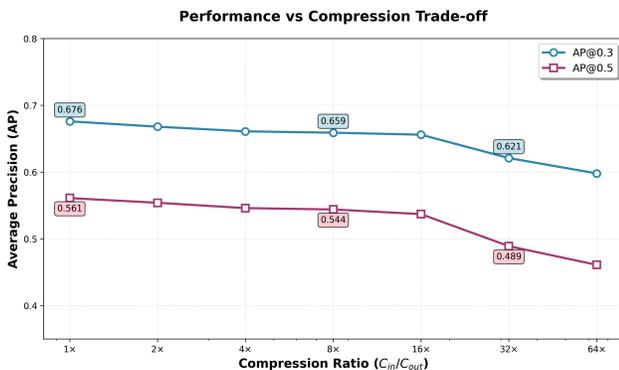


Figure 4. Performance vs compression trade-off analysis on V2X-Real dataset. FocalComm maintains robust performance up to 8x compression with minimal degradation, demonstrating effective communication efficiency for practical V2X deployment.

duction in AP@0.5 (from 56.1% to 54.4%). Even at aggressive 32x compression, the method retains 62.1% AP@0.3 and 48.9% AP@0.5, demonstrating the effectiveness of our hard instance-focused feature selection. This analysis validates that FocalComm can operate efficiently under bandwidth constraints while maintaining strong detection performance, making it practical for real-world V2X deployment scenarios.

5. Conclusion

We presented FocalComm, a novel multi-agent collaborative perception framework that prioritizes hard instance-

Method	Car	Pedestrian	Truck	Overall
No Collaboration	73.7/68.4	31.8/13.9	21.2/15.7	42.2/32.7
<i>Component Analysis</i>				
+ Collab (baseline)	88.3/85.6	47.8/22.7	47.9/46.1	61.3/51.4
+ Collab + HIM	91.5/88.8	54.6/26.6	52.6/48.7	66.2/54.7
+ Collab + QAFF	91.2/88.2	52.7/23.7	48.7/45.1	65.5/54.0
Full Model (+ Both)	91.5/89.6	57.4/27.3	53.9/51.6	67.6/56.1

Table 3. Ablation studies on V2X-Real test set for the vehicle-centric approach. Results show AP@0.3/AP@0.5 for each class.

aware feature exchange. Our progressive HIM module and QAFF mechanism achieve state-of-the-art results 67.6% mAP@0.3 on V2X-Real (5.6% improvement) with strong performance in both V2V (64.8%) and I2I (70.2%) scenarios. FocalComm excels at safety-critical pedestrian detection (57.4% AP@0.3, 80% relative improvement) while maintaining robust performance under 8x compression.

Limitations. Our evaluation focuses on LiDAR-based datasets; extending to camera-only or multimodal fusion remains future work, along with formal theoretical analysis of HIM convergence and evaluation under adverse weather conditions. Future work will explore hard-instance aware message packing, multimodal extensions, and theoretical grounding for real-world V2X deployment.

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