CoBEVT: Cooperative Bird’s Eye View Semantic Segmentation with Sparse Transformers

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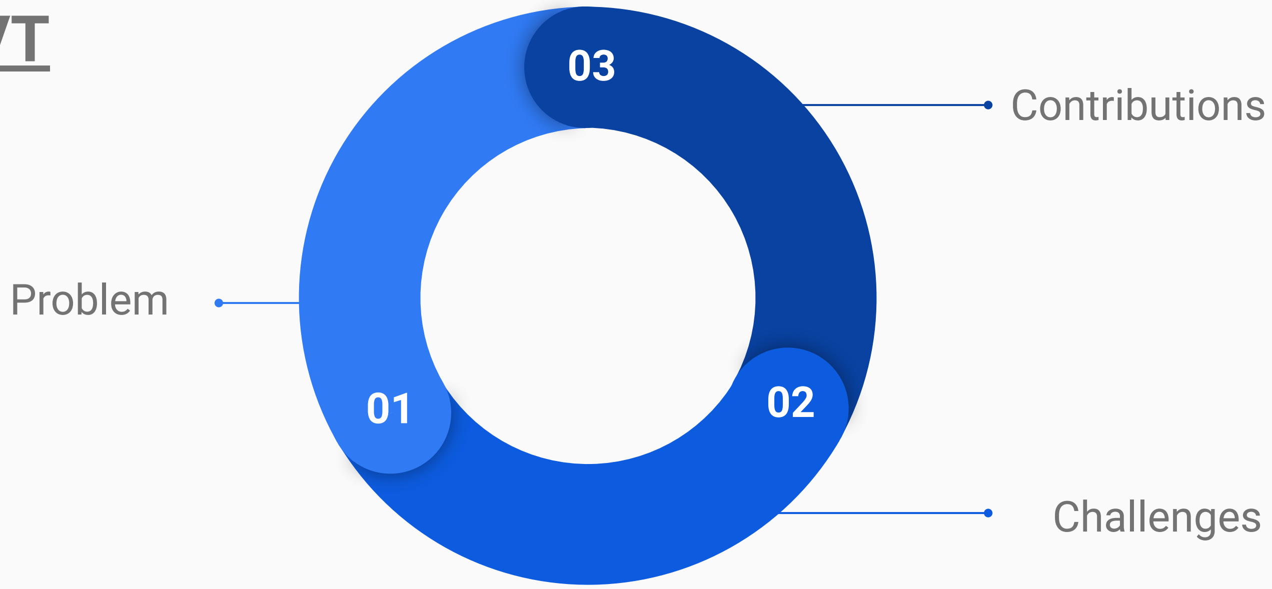
Introduction

CoBEVT



Introduction

Problem

01

Addresses single-agent based systems:

- Limitations in handling occlusions
- Limitations in detecting distant objects
- Vulnerable to system malfunctions

Introduction

- Objects are hidden from single-agent systems that cannot detect beyond their sensor capabilities
- Real world traffic is highly variable and highly unpredictability
- Camera sensors often lack in distant object perception

02

Challenges

- **CoBEVT** is the first multi-agent multi-camera perception framework designed for BEV semantic labeling

03

Contributions

- Fused Axial Attention (**FAX**) Module is used for local and global spatial interactions across views and agents

- Demonstrated SOTA results on OPV2V with superior performance over existing models

Design Details

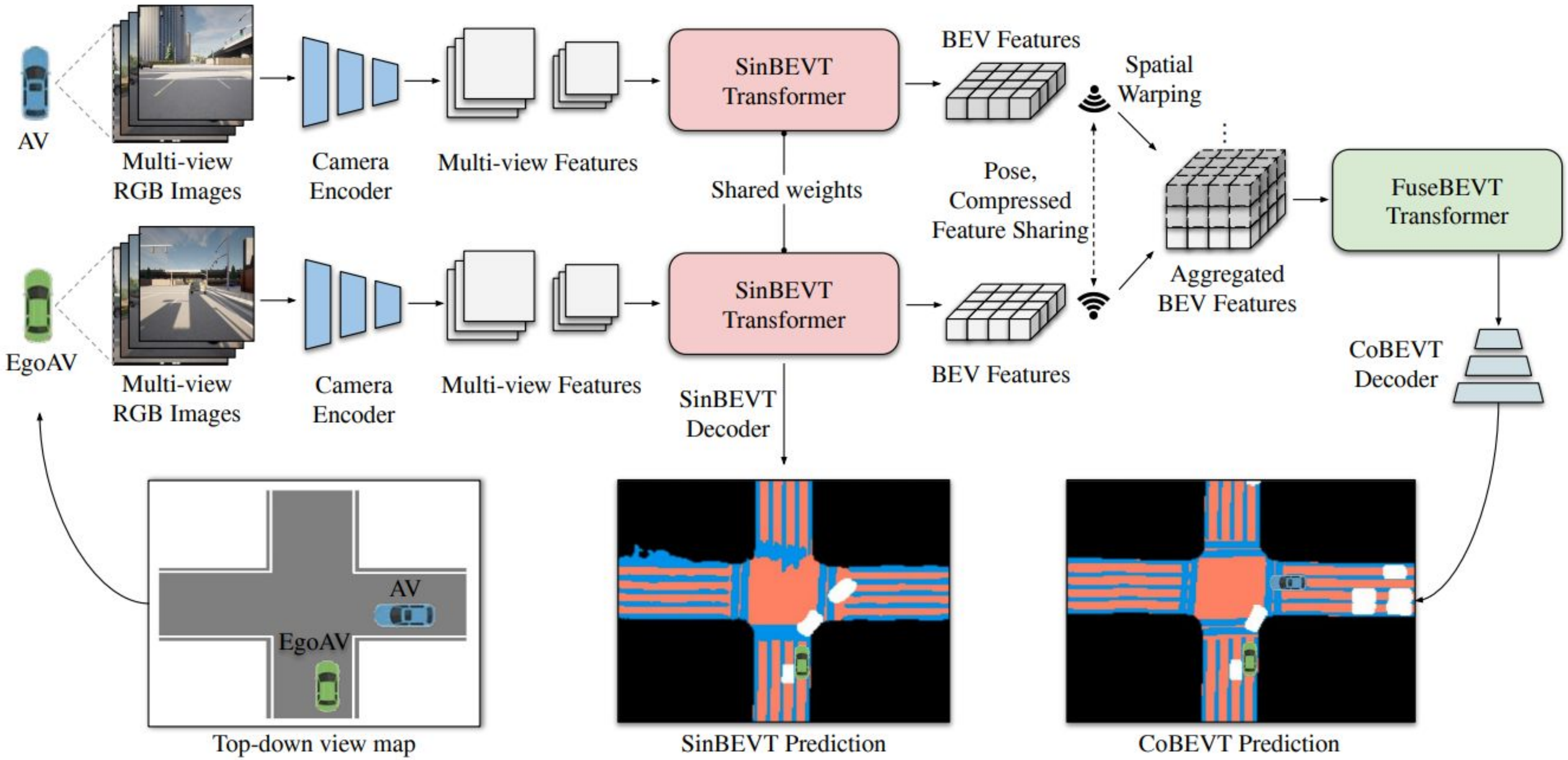


Figure 1: The overall framework of CoBEVT.

Design Details

Step 1	Step 2	Step 3	Step 4	Step 5
Multi-View Camera Inputs and Encoding	**SinBEVT** for Single-Agent BEV Feature Computation	Feature Sharing and Transformation	**FuseBEVT** for Multi-Agent BEV Feature Fusion	Final Aggregation and Decoding

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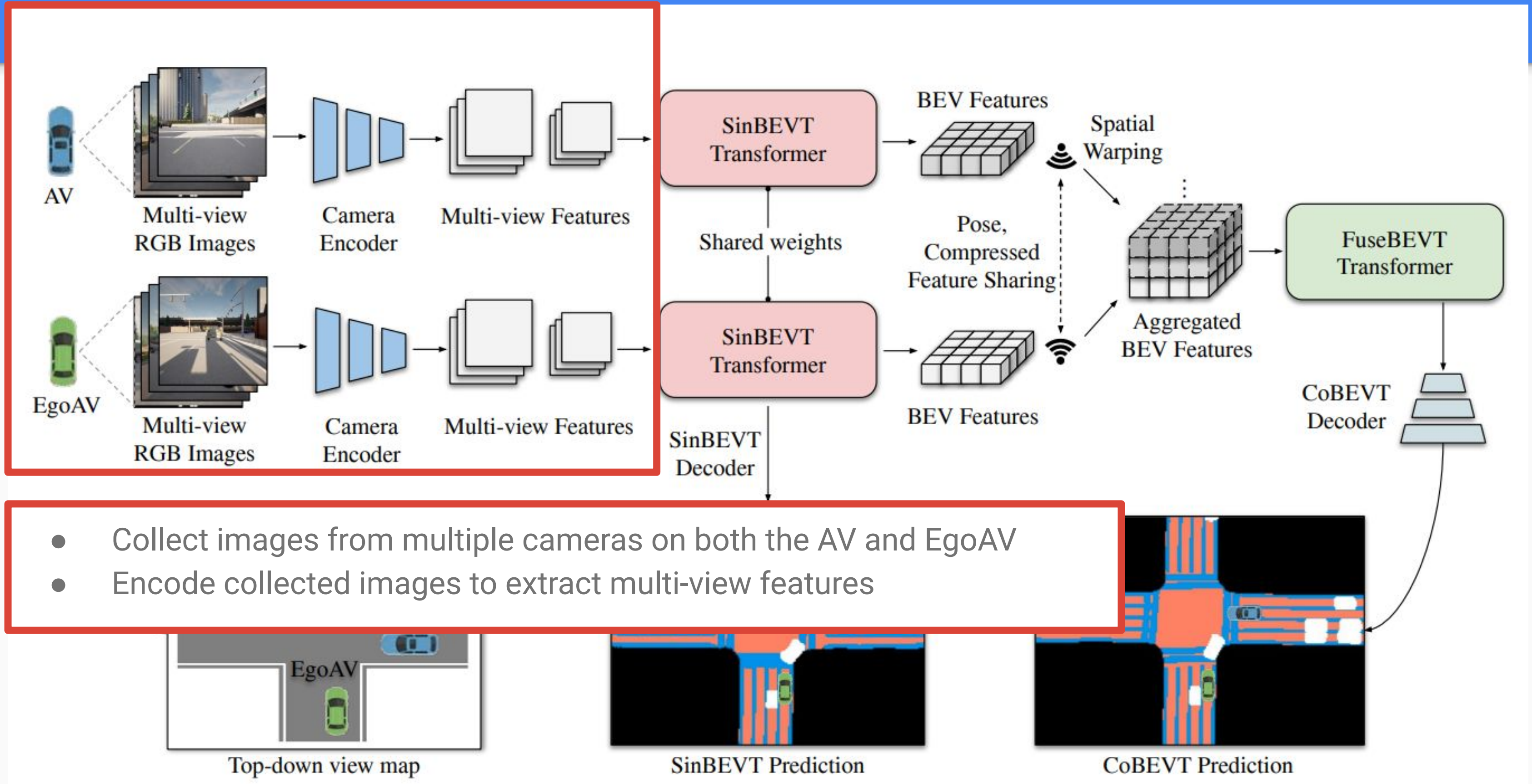

- Collect images from multiple cameras on both the AV and EgoAV
- Encode collected images to extract multi-view features

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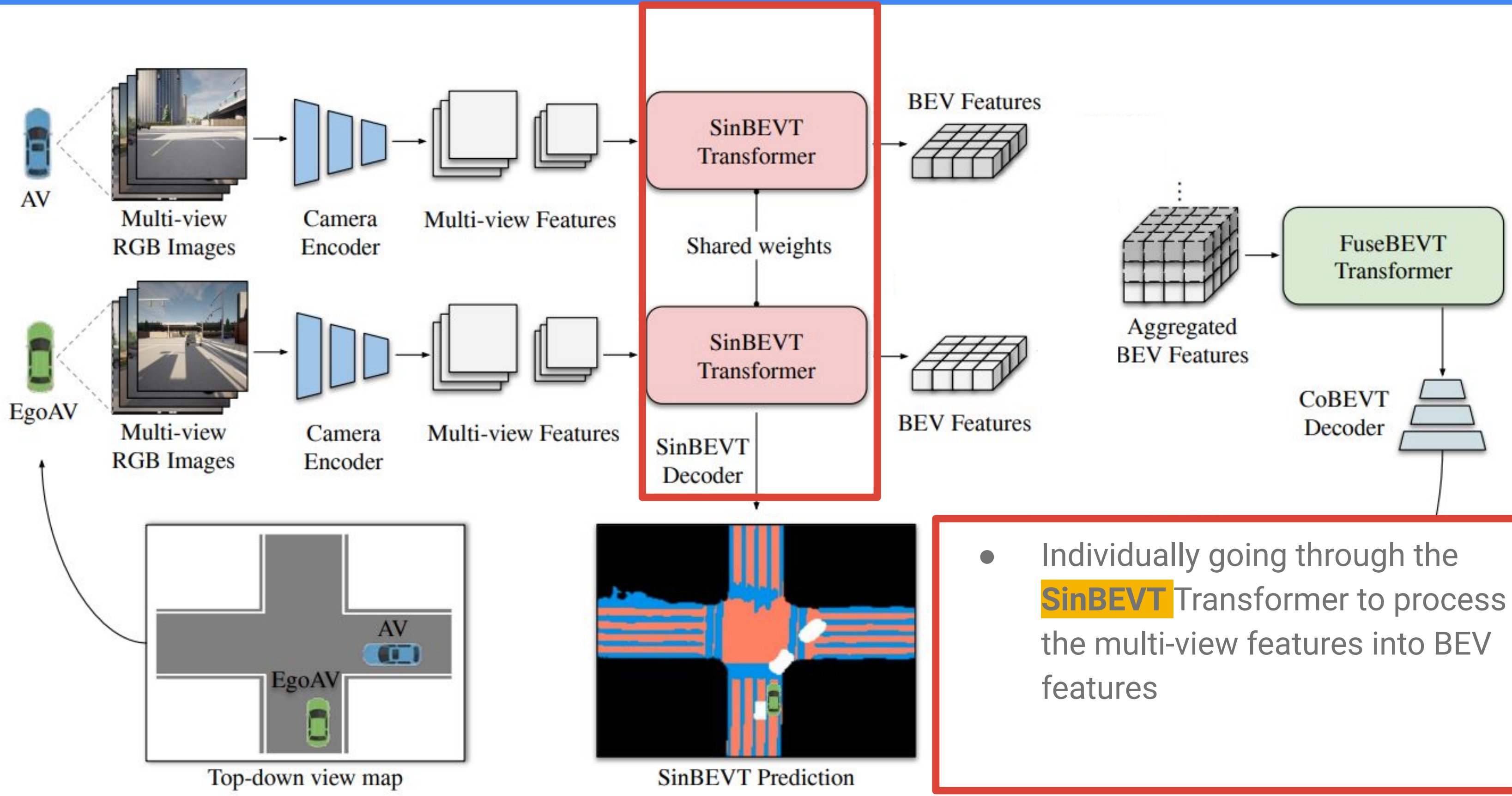

Figure 1: The overall framework of CoBEVT.

- Individually going through the SinBEVT Transformer to process the multi-view features into BEV features

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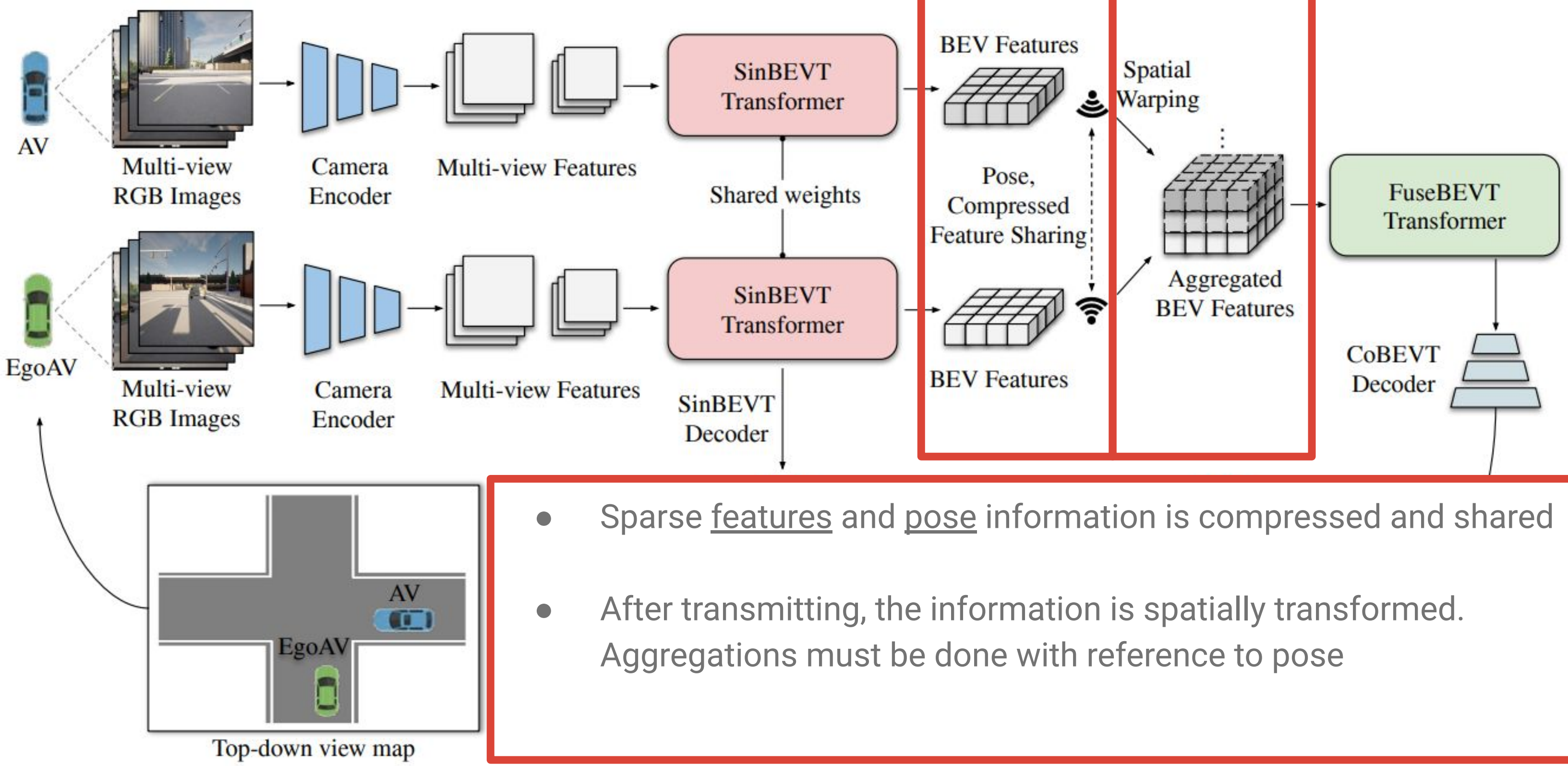

- Sparse features and pose information is compressed and shared
- After transmitting, the information is spatially transformed. Aggregations must be done with reference to pose

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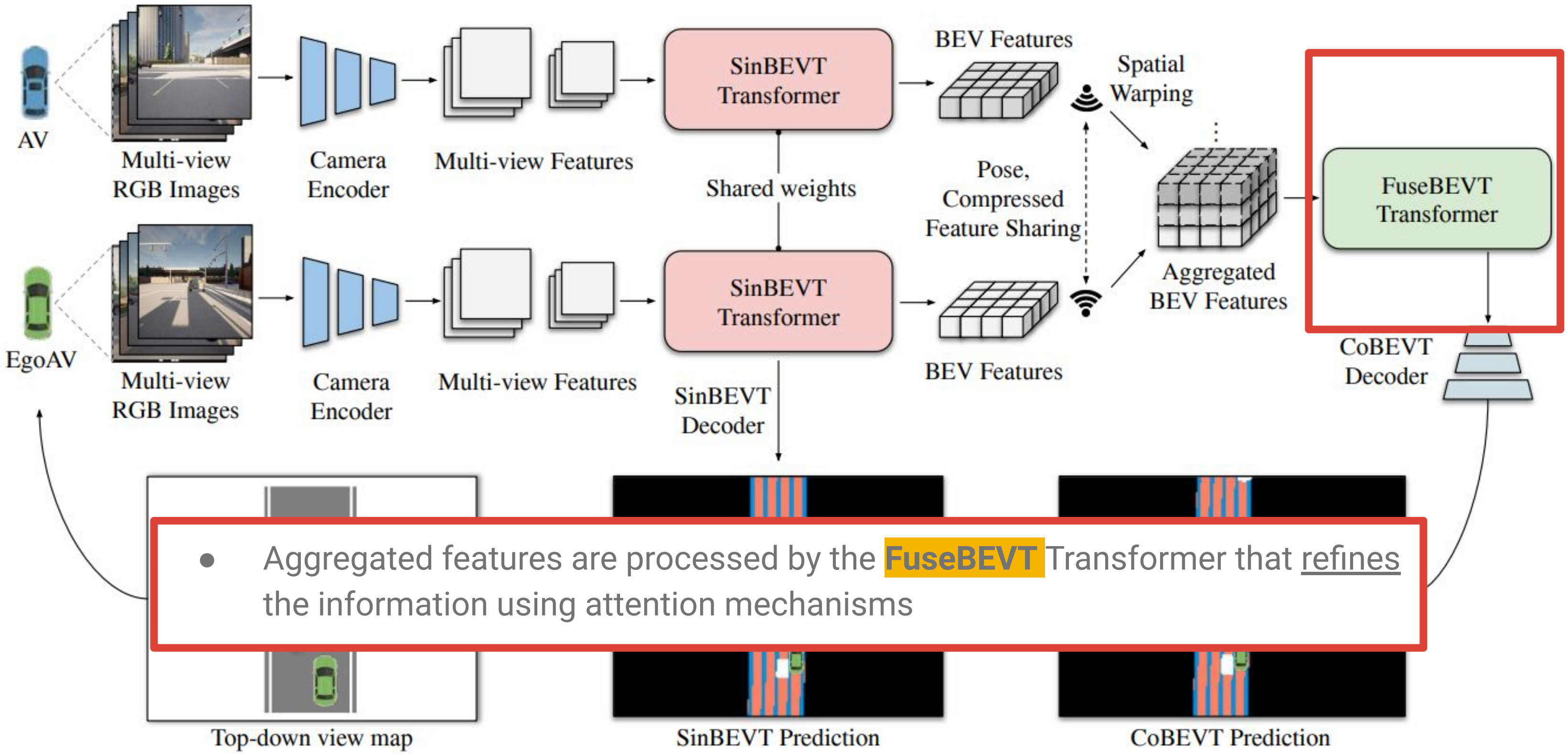

- Aggregated features are processed by the **FuseBEVT** Transformer that refines the information using attention mechanisms

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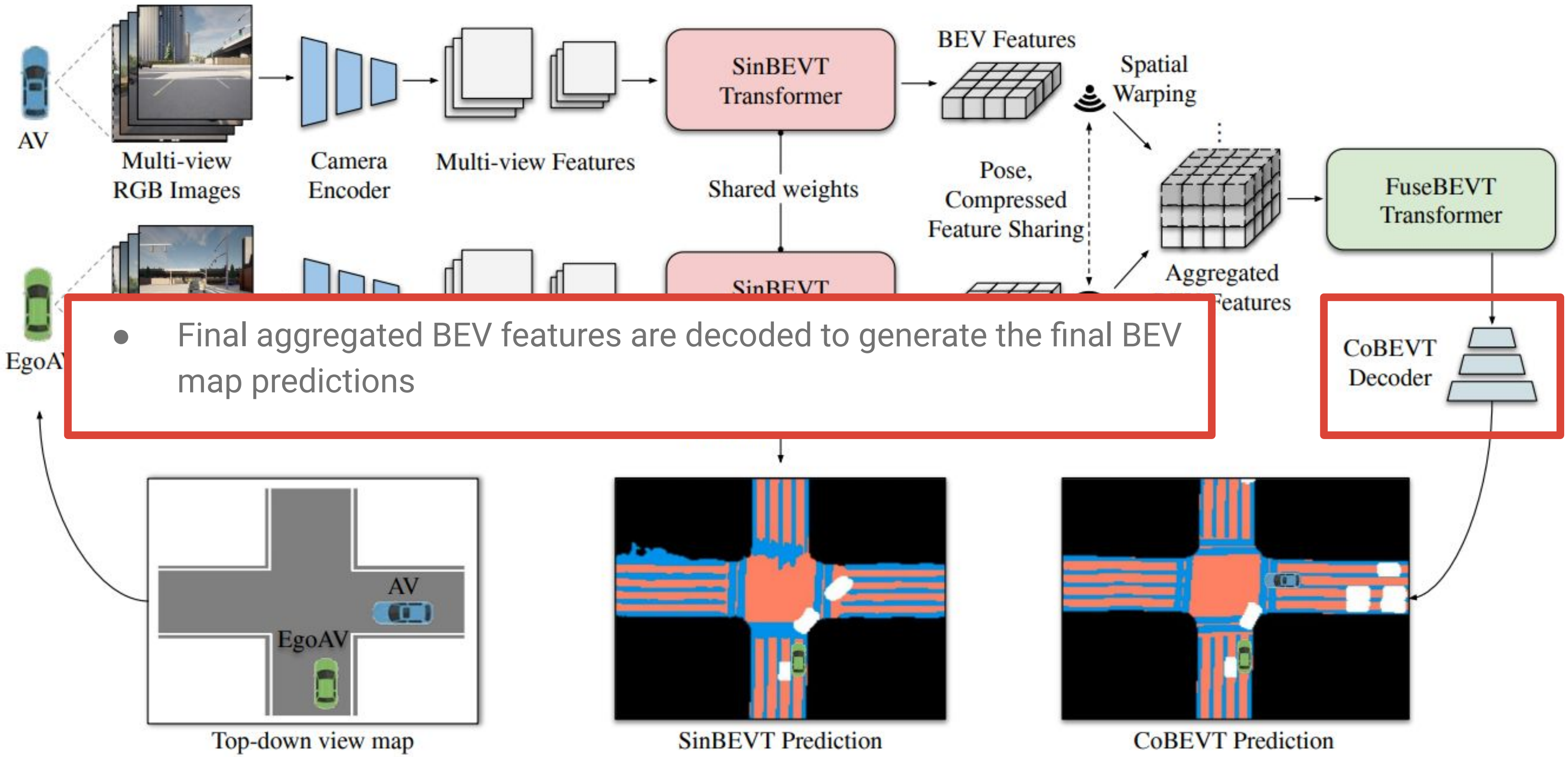

- Final aggregated BEV features are decoded to generate the final BEV map predictions

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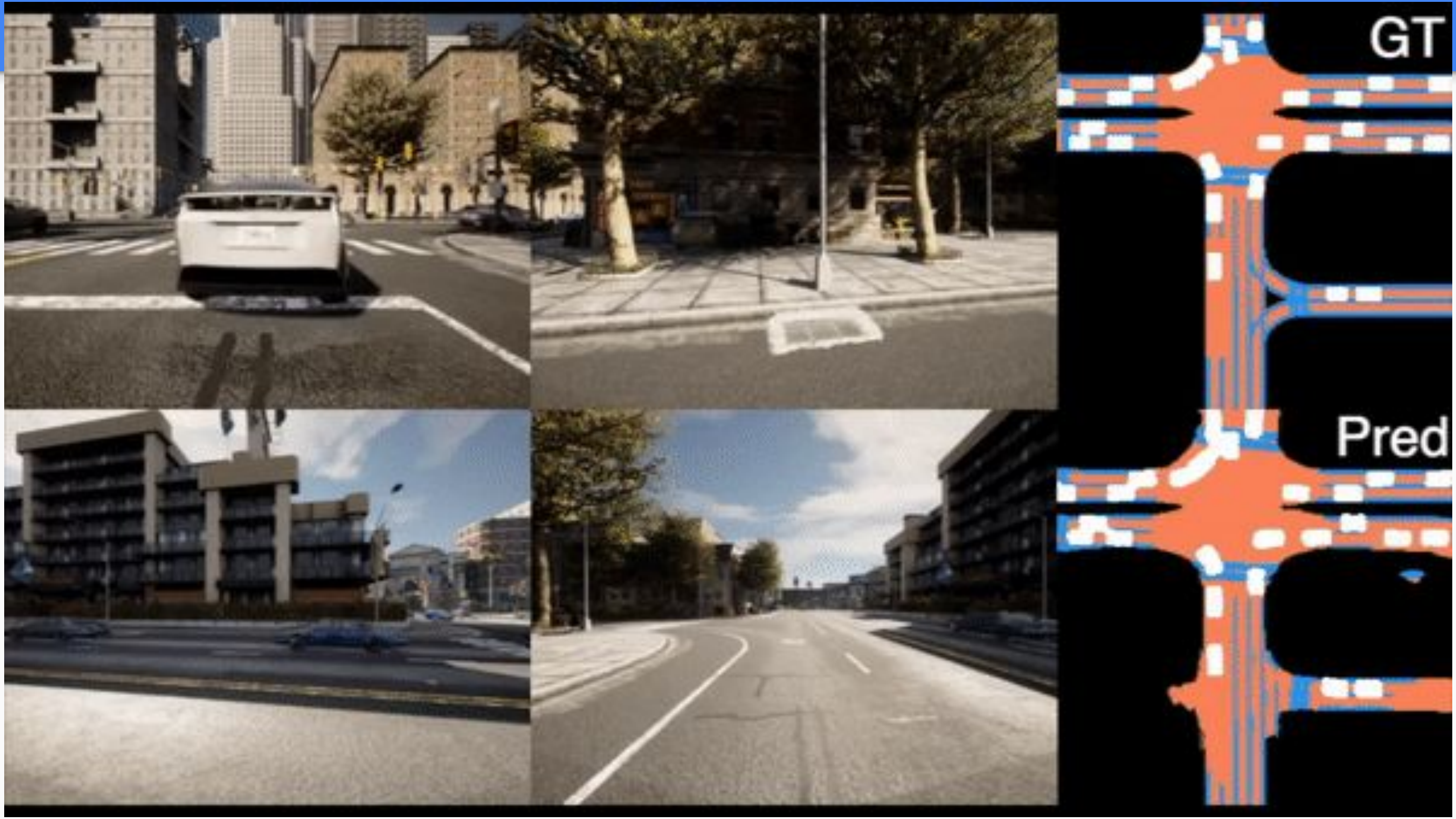


OPV2V: Multi-agent BEV map prediction.

Design Details

Step 2

SinBEVT for Single-Agent BEV Feature Computation

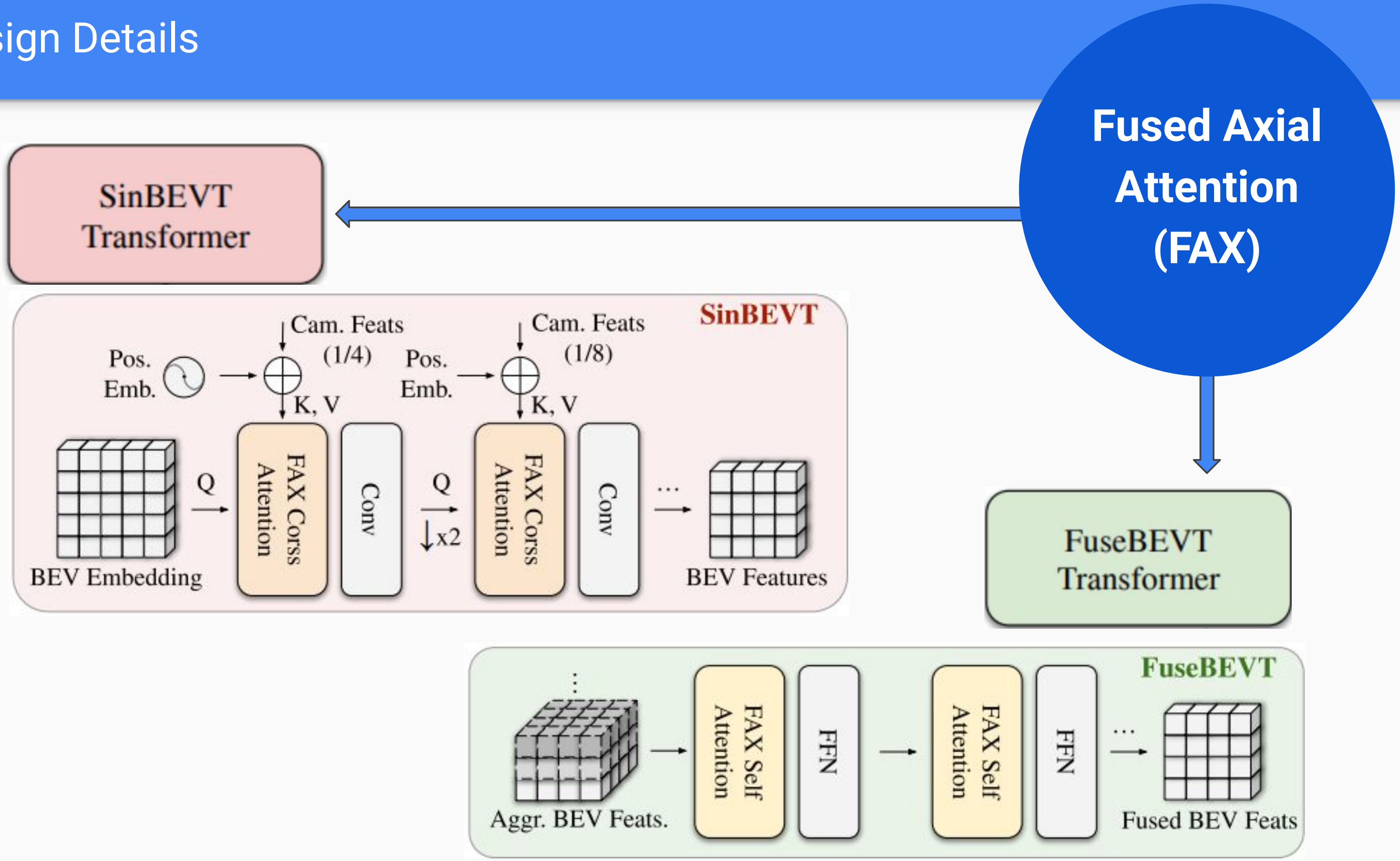
SinBEVT Transformer

Step 4

FuseBEVT for Multi-Agent BEV Feature Fusion

FuseBEVT Transformer

Design Details



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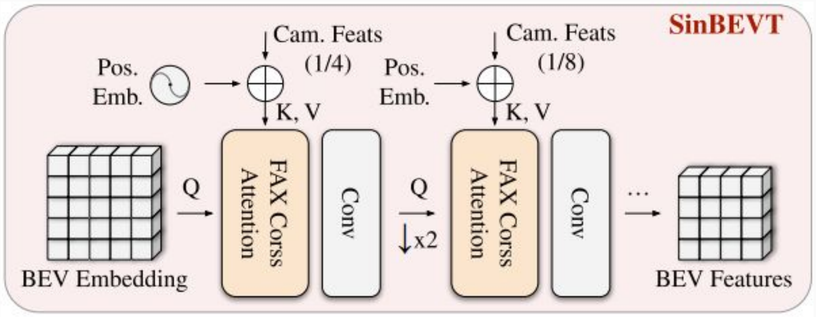


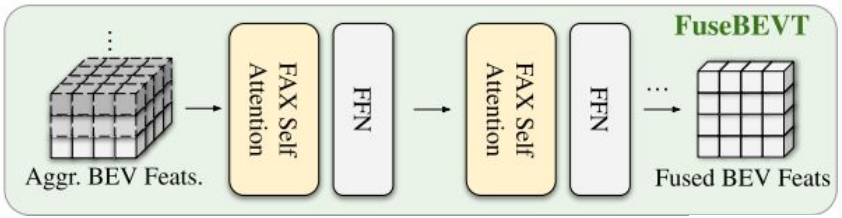
$$\text{3D-Rel-Attention}(\mathbf{Q},\mathbf{K},\mathbf{V}) = \text{softmax}(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}} + \mathbf{B})\mathbf{V},$$

Q, K, V = query, key, value matrices projected from the input tensor

B = relative position bias

$$\hat{\mathbf{B}} \in \mathbb{R}^{(2N-1)\times(2H-1)\times(2W-1)}$$

1. Initialize BEV embedding as Q
2. Positional info and camera features are added (K&V)
3. Q*KV go through FAX to process hi-res features
4. Second pass focuses on low-res features
5. BEV Features



Preprocessing:

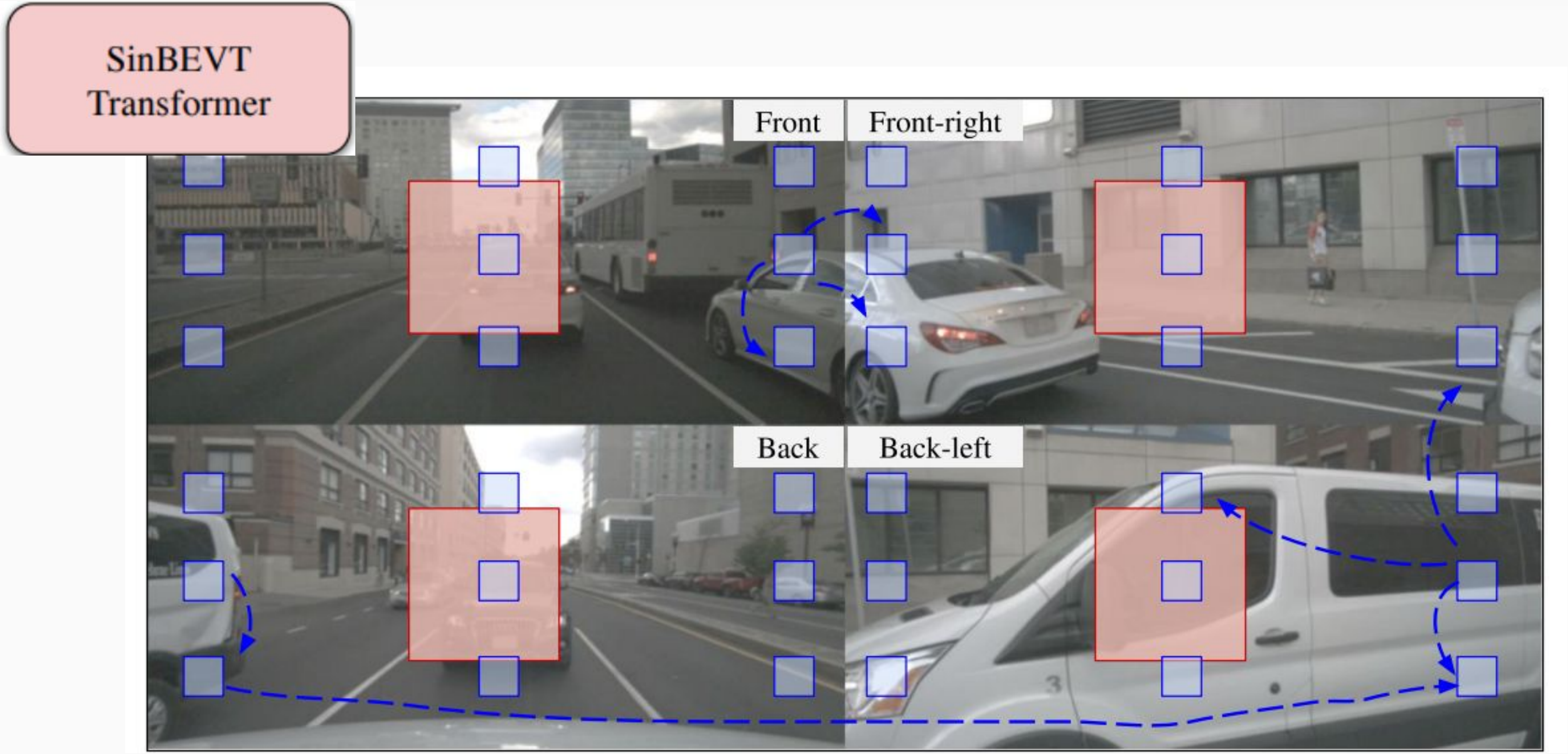
$$\text{Fused-Block}: (N,H,W,C) \to (N, \frac{H}{P}\times P, \frac{W}{P}\times P, C) \to (\frac{HW}{P^2}, \underbrace{N\times P^2}_{\text{“spatial axis”}}, C)$$

$$\text{Fused-Grid}: (N,H,W,C)\to(N, G\times\frac{H}{G}, G\times\frac{W}{G}, C)\to\underbrace{(N\times G^2, \frac{HW}{G^2}, C)\to(\frac{HW}{G^2}, N\times G^2, C)}_{\text{swapaxes(axis1=-2,axis2=-3)}}$$

0. Preprocessing " … define the Fused-Block(·) operator with parameter P as partitioning the input 3D feature x ∈ R^{N×H×W×C} into non-overlapping 3D windows … N × P × P."

1. Aggregated BEV features
2. FAX captures local and global interactions
3. Second pass is for FAX feature enhancement and refinement
4. Fused BEV Features

Design Details



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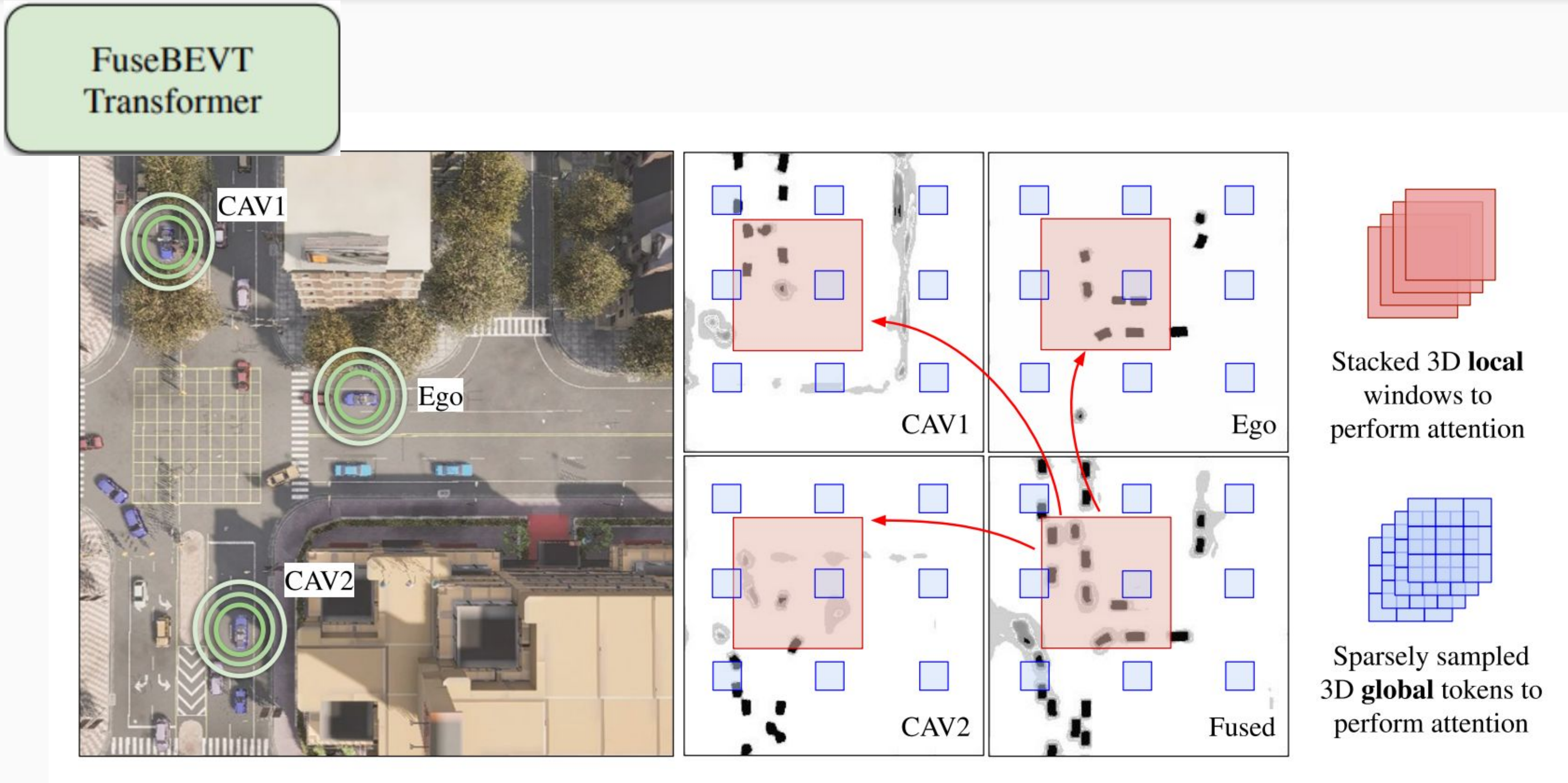

Evaluations

Evaluations

Notes:

- CoBEVT is insensitive to compression and still beats other fusion methods @64cpr
- SinBEVT approach achieves SOTA performance with real-time inference speed
- Not limited to cameras i.e. radar, LiDAR

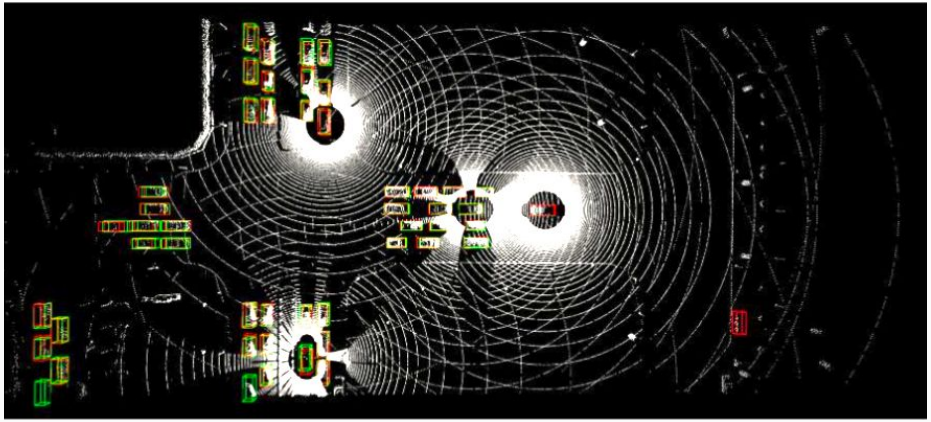

Table 4: Compression effect on OPV2V Camera.

CPR-rate	Size (KB)	IoU
0x	524	60.4
8x	66	60.1
16x	33	58.9
32x	16	56.2
64x	8	54.8

Evaluations

Experiment Setup

Datasets:

- OPV2V
- nuScenes

Evaluation Metrics:

- IoU
- AP

Table 1: **Map-view segmentation on OPV2V camera-track.** We report IoU for all classes. All fusion methods employs CVT [3] backbone, except for CoBEVT which uses SinBEVT backbone.

Method	Veh.	Dr.Area	Lane
No Fusion	37.7	57.8	43.7
Map Fusion	45.1	60.0	44.1
F-Cooper [21]	52.5	60.4	46.5
AttFuse [12]	51.9	60.5	46.2
V2VNet [20]	53.5	60.2	47.5
DiscoNet [14]	52.9	60.7	45.8
FuseBEVT	**59.0**	**62.1**	**49.2**
CoBEVT	**60.4**	**63.0**	**53.0**

Table 2: **3D detection results on the OPV2V LiDAR-track.** All methods employ PointPillar [61] backbone. (C) denotes using 64× feature compression.

Method	AP0.7	AP0.7(C)
No Fusion	60.2	60.2
Late Fusion	78.1	78.1
Early Fusion	80.0	-
F-Cooper	79.0	78.8
AttFuse	81.5	81.0
V2VNet	82.2	81.4
DiscoNet	83.6	83.1
FuseBEVT	**85.2**	**84.9**

Table 3: **Vehicle map-view segmentation on nuScenes.** All models use only a single time-stamp. $*$ denotes our reproduced result with EfficientNet-b4 backbone.

Method	Veh.	Par(M)	FPS
VPN* [27]	29.3	4.	31
OFT [59]	30.1	-	-
Lift-Splat	32.1	14	25
FIERY [4]	35.8	7	8
CVT [3]	36.0	1.2	35
SinBEVT	**37.1**	1.6	35

Evaluations

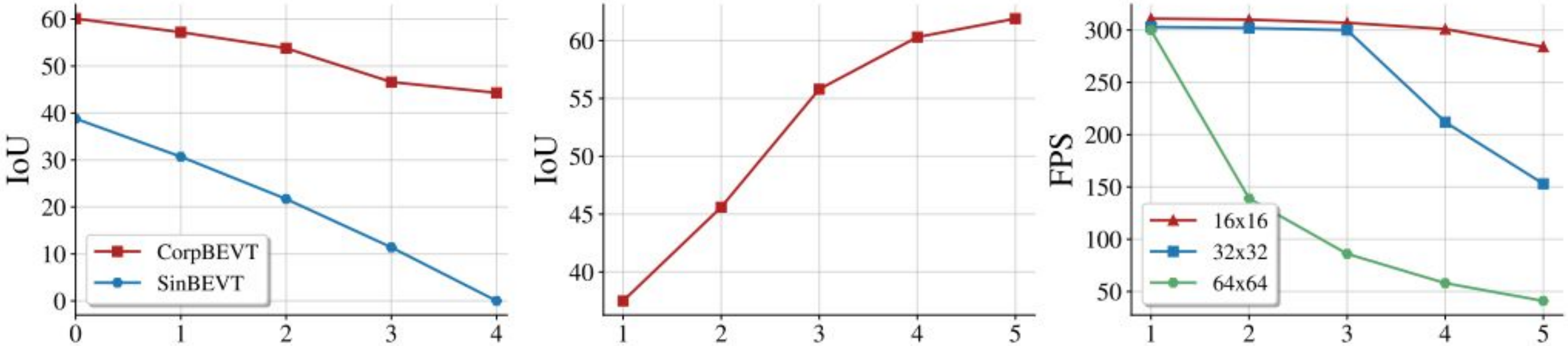

Figure 5: **Ablation studies.** (a) IoU *vs.* number of dropped cameras (b) IoU *vs.* number of agents. (c) FPS *vs.* number of agents. The channel dimension of BEV feature map is fixed as 128 for (c).

IoU

FPS @ higher feature map resolutions

Comparisons

Comparisons

The V2X Communication approach essentially utilizes multi-agent, multi-sensors data to enhance perception. However the following methods differ in the following ways:

AVR: Augmented Vehicular Reality

- Focuses on extending visual range by sharing 3D sensor data between agents

V2VNet: Vehicle-to-Vehicle Communication for Joint Perception and Prediction

- Uses Graph Neural Network (GNN) to improve detection and motion forecasting

COOPERNAUT: End-to-End Driving with Cooperative Perception for Networked Vehicles

- Uses V2V to share encoded LiDAR data using Point Transformers for better decision making

BEVFusion: Multi-Task Multi-Sensor Fusion with Unified Bird's-Eye View Representation

- Focuses on fast and efficient processing of converting camera data to a BEV representation

Conclusion

- CoBEVT introduces a **multi-agent, multi-camera** perception framework designed for BEV semantic labeling using sparse transformers and data fusion

- Future work aims to address common V2V challenges like asynchronization, positional errors, and noise

Questions?