# ROSCENE: A LARGE SCALE MULTI-VIEW 3D DATASET FOR ROADSIDE PERCEPTION

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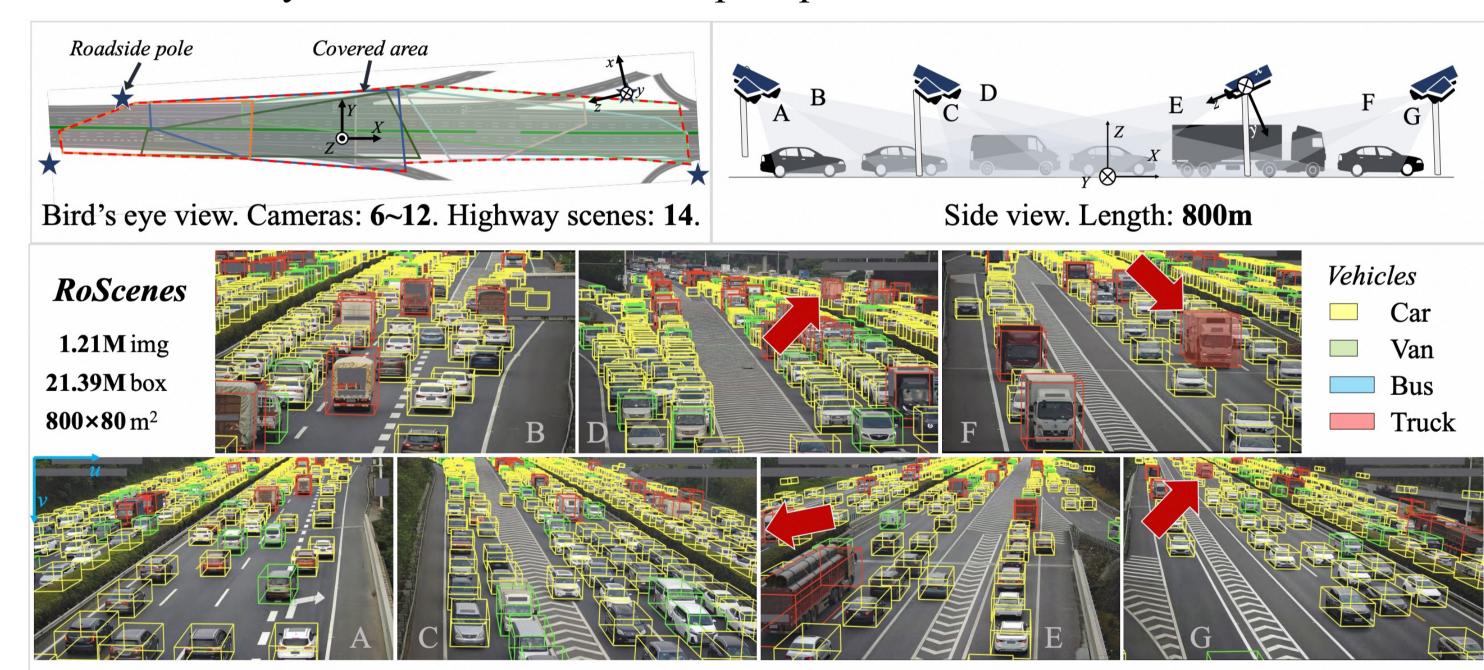


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## **OVERVIEW**

Dataset	Year	Ty V	pe I	Cam	$rac{ m BEV~area}{(m^2)}$	$\begin{array}{c} \text{Duration} \\ (hour) \end{array}$	$\frac{\text{Dive}}{\text{Night}}$		Image	Box	Class
KITTI [10]	2012	<b>√</b>	_	2	$70 \times 80$	1.5	$\checkmark$	_	0.02M	0.08M	8
ApolloScape [16]	2019	<b>√</b>	-	6	-	2.5	$\checkmark$	_	0.14M	0.07M	8-35
nuScenes [1]	2019	$\checkmark$	-	6	$100 \times 100$	5.5	$\checkmark$	$\checkmark$	1.40M	1.40M	23
Argoverse[4]	2020	$\checkmark$	-	7	$205 \times 155$	320.0	$\checkmark$	$\checkmark$	0.02M	0.99M	15
Waymo Open [9]	2020	$\checkmark$	-	5	$150 \times 150$	6.4	$\checkmark$	$\checkmark$	0.23M	12.00M	4
ONCE [25]	2021	$\checkmark$	-	7	$200\times200$	144.0	$\checkmark$	$\checkmark$	7.00M	0.42M	5
Rope3D [38]	2022	-	<b>√</b>	1	$104 \times 102$	_	<b>√</b>	<b>√</b>	0.05M	1.50M	12
V2X-Seq $[40]$	2023	$\checkmark$	$\checkmark$	1 + 1	$104 \times 102$	0.4	-	$\checkmark$	0.07M	1.20M	10
A9 [5]	2023	-	$\checkmark$	4	-	0.1	-	$\checkmark$	0.01M	0.21M	9
RoScenes (Ours)	_	_	✓	$6\!\sim\!12$	800 × 80	23.9	✓	-	<b>1.30M</b>	21.13M	4

Quantitative comparison with the published vehicle-side and infrastructureside 3D datasets. Our dataset achieves the largest BEV perception area and the largest number of annotations. Type: V: Vehicle-side sensors. I: Infrastructure-side sensors. "Cam" is the number of synchronized cameras adopted per scene



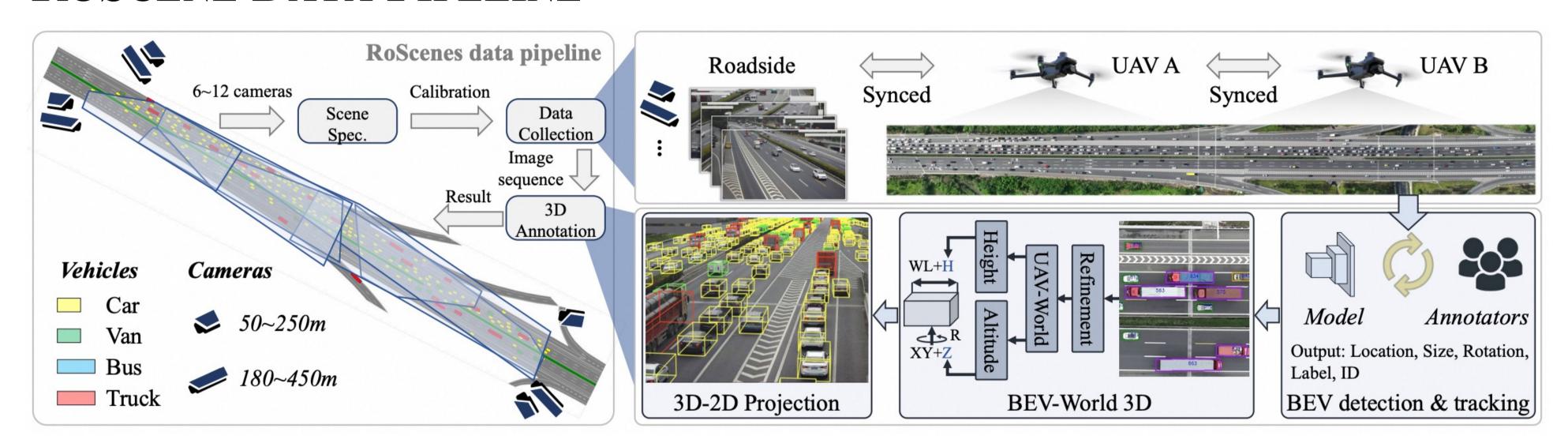
Perspective view. Truck invisible: A, B, C; small: G; occluded: D, E; clear: F.

Demonstration of our RoScenes dataset. The annotated truck is difficult to recognize in A, B, C, E, F, G, but is clear in D.

#### Contribution

- 1) A large-scale multi-view 3D dataset for roadside perception, with a novel, cost-effective annotation pipeline is introduced to obtain 3D annotations in challenging traffic scenarios.
- 2) A method RoBEV that effectively aggregates 2D image feature to 3D detection queries via feature-guided position embedding.
- 3) The extensive experimental evaluation also indicates the RoScenes dataset can serve as a benchmark for BEV architectures in the future.

## ROSCENE DATA PIPELINE



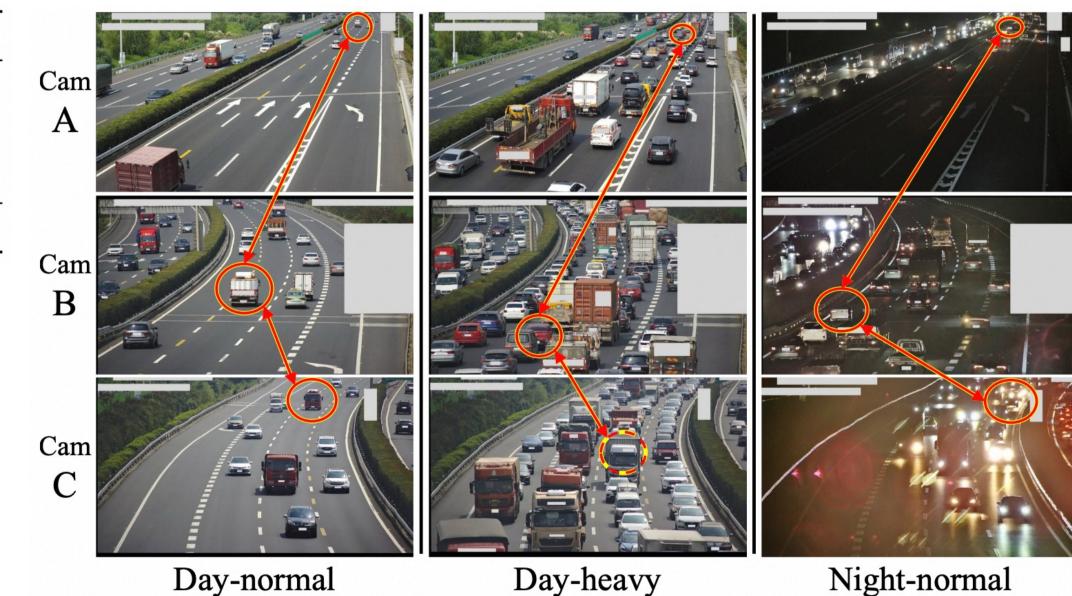
Overall data collection and annotation pipeline. We propose BEV-to-3D joint annotation for efficiency.

- 1) A couple of UAVs hover the target scene to capture aerial image sequence along with roadside camera sequence synchronously;
- 2) We train the UAV model consists of BEV detector and tracker on UAV images for generating image-level BEV annotations, which are then transformed to the XY plane of World Coordinate via the UAV-to-World homography matrix;
- 3) To further access the altitude and height of each annotated vehicle for converting BEV 2D boxes to world 3D boxes, we choose the center of BEV 2D boxes to query the altitude in pre-built 3D reconstruction model and attach vehicle's height to the average height of its class label;
- 4) We perform the perspective projection of 8 corners of 3D boxes onto 2D image planes for all roadside cameras using the camera parameters.

Scene	$\operatorname{Train}$	Easy	$\operatorname{Hard}$	Test (Unseen)		
#001 #002 #003 #004	329(138k)  534(256k)  306(129k)  534(257k)	$51(21k) \\ 83(40k) \\ 48(20k) \\ 80(40k)$	$51(21k) \\ 83(40k) \\ 48(20k) \\ 80(40k)$	$\#005 \sim \#014$		
Sum	1,703(779k)	265(121k)	265(121k)	637(274k)		

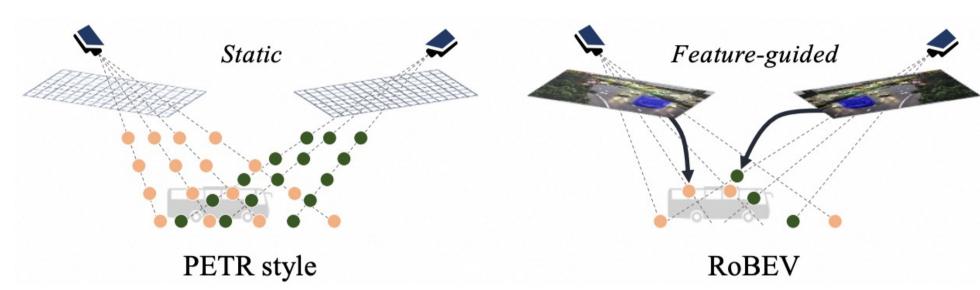
Train, validation (easy, hard) and unseen test splits for benchmark. (Clips and images)



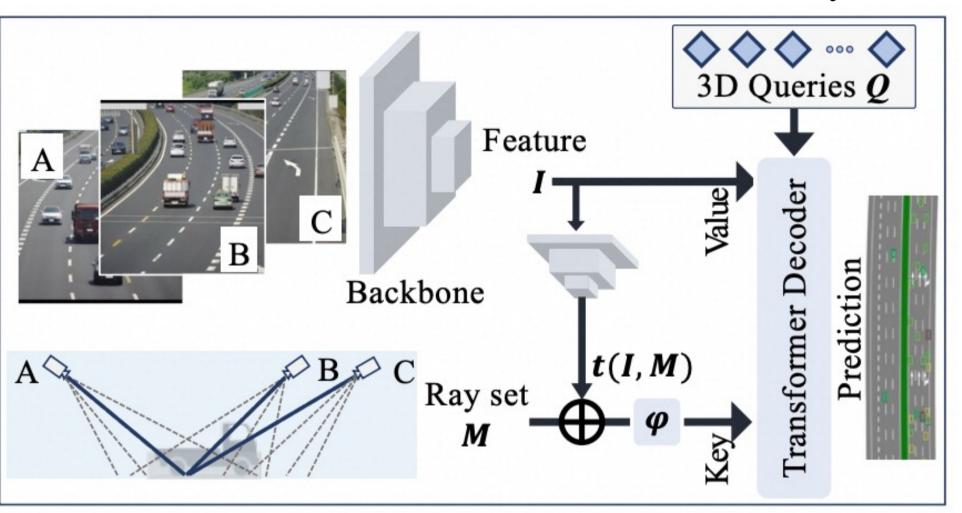


Multi-view images under different conditions. Connected vehicles are identical.

### ROBEV PERCEPTION ALGORITHM



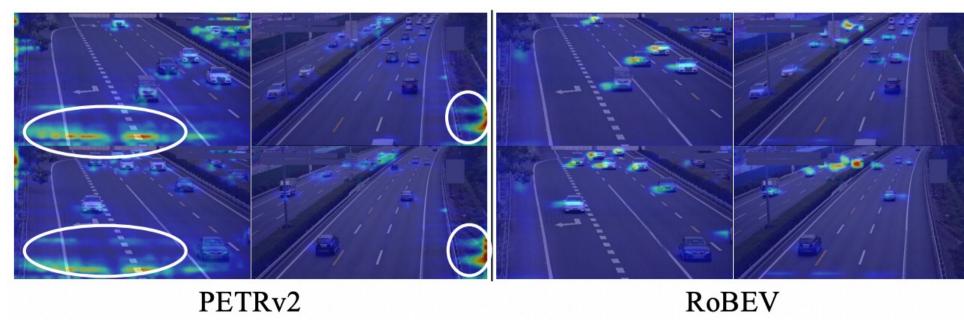
Previous methods learn positional encoding  $\phi(\cdot)$  which constrained to the specific camera view, without taking into account the variations of different camera layouts



Our RoBEV has an enhanced feature-guided position embedding that leverages contextual information from images to augment feature assignment process.

Method	Easy						Hard				
Wicollod	$\overline{\mathrm{NDS}}$	mAP	mATE	mASE	mAOE	$\overline{\mathrm{NDS}}$	mAP	mATE	mASE	mAOE	NDS
BEVDet [18]	0.506	0.299	0.742	0.079	0.042	0.445	0.184	0.754	0.087	0.043	0.476
BEVDet [18] BEVDet4D [17]	0.428	0.200	0.896	0.094	0.041	0.393	0.139	0.922	0.099	0.038	0.411
SOLOFusion [32]	0.308	0.129	0.878	0.144	0.517	0.202	0.066	0.844	0.144	1.000	0.255
BEVFormer [23]	0.693	0.609	0.560	0.078	0.030	0.597	0.433	0.600	0.090	0.029	0.645
DETR3D [43]	0.722	0.644	0.501	0.067	0.031	0.633	0.471	0.508	0.080	0.028	0.678
PETRv2 [27]	0.674	0.587	0.590	0.090	0.032	0.580	0.414	0.633	0.100	0.029	0.627
StreamPETR [41]	0.619	0.513	0.690	0.102	0.032	0.496	0.284	0.739	0.107	0.031	0.558
RoBEV (Ours)	0.753	0.684	0.442	0.058	0.031	$\boldsymbol{0.672}$	0.524	0.438	0.077	0.027	0.713

Performance comparison of BEV methods on RoScenes dataset. RoBEV achieve state-of-the-art performance.



Attention heatmap visualization. PETRv2 has static artifacts in heatmap across scenes and cameras.