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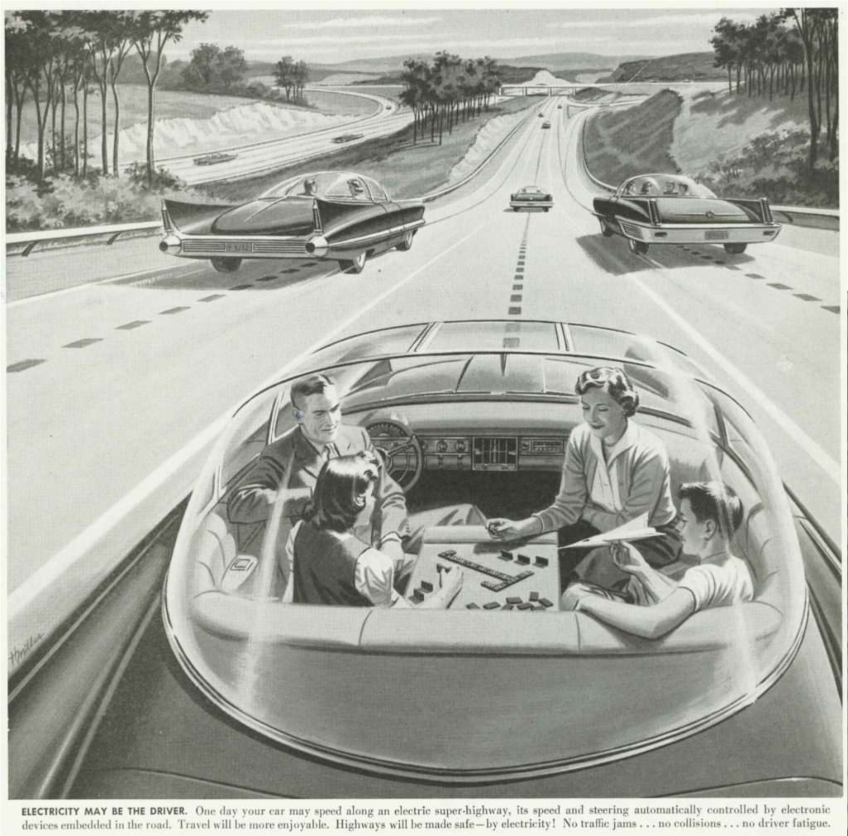
Are We Ready for *Snow-tonomous Driving*?

Toward Robust Automated Driving in Extreme Weather

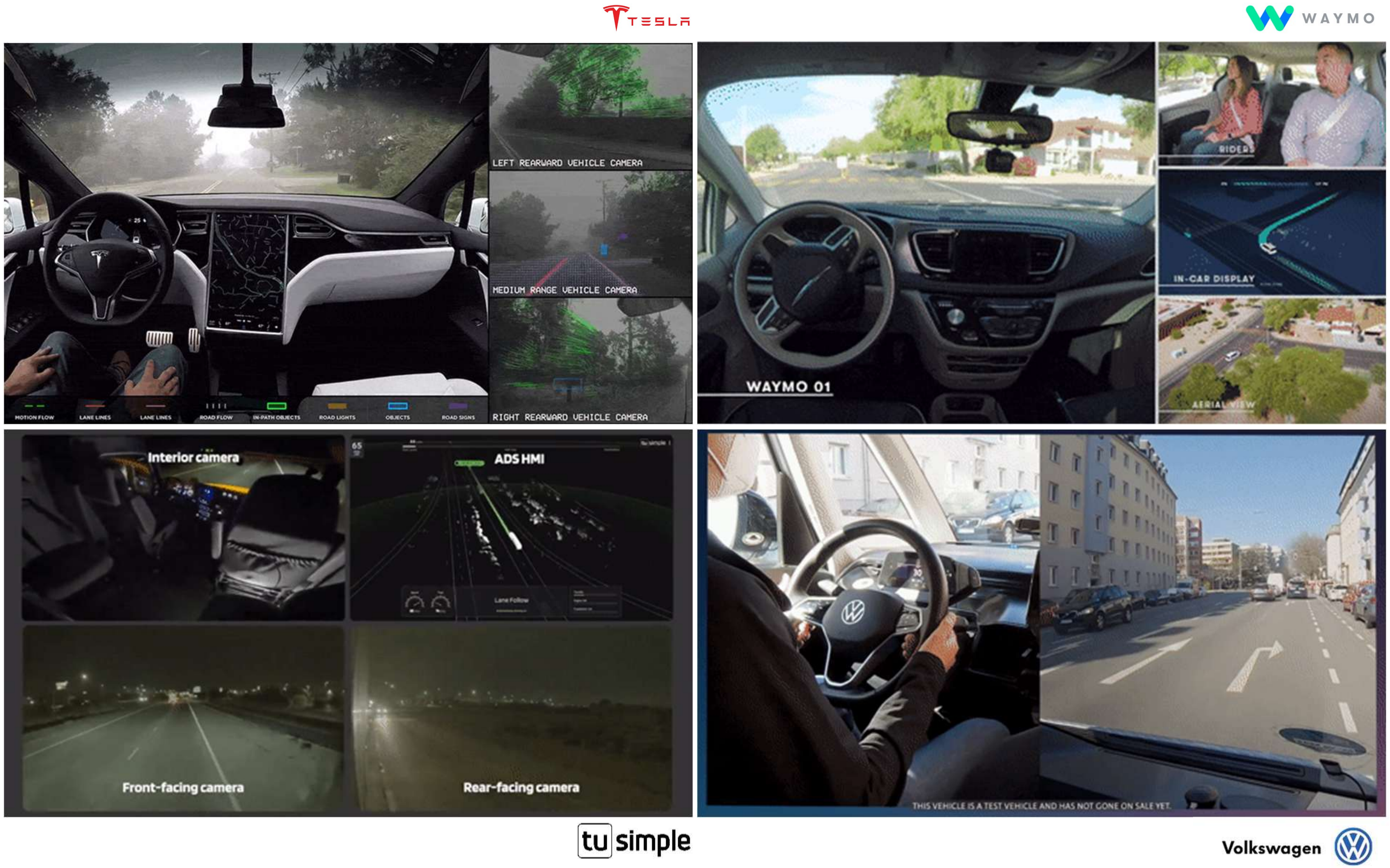
EREN ERDAL AKSOY, LUND UNIVERSITY



Driverless Car of the Future, advertisement for "*America's Electric Light and Power Companies*", Saturday Evening Post, 1950s.

Credit: The Everett Collection

In the 1980s, German pioneer Ernst Dickmanns introduced a Mercedes van to drive *hundreds of kilometers autonomously on a highway*!



Not every kilometer driven is equal: **Most automated vehicles have been primarily trained and tested under optimal weather and road conditions with clear visibility!**

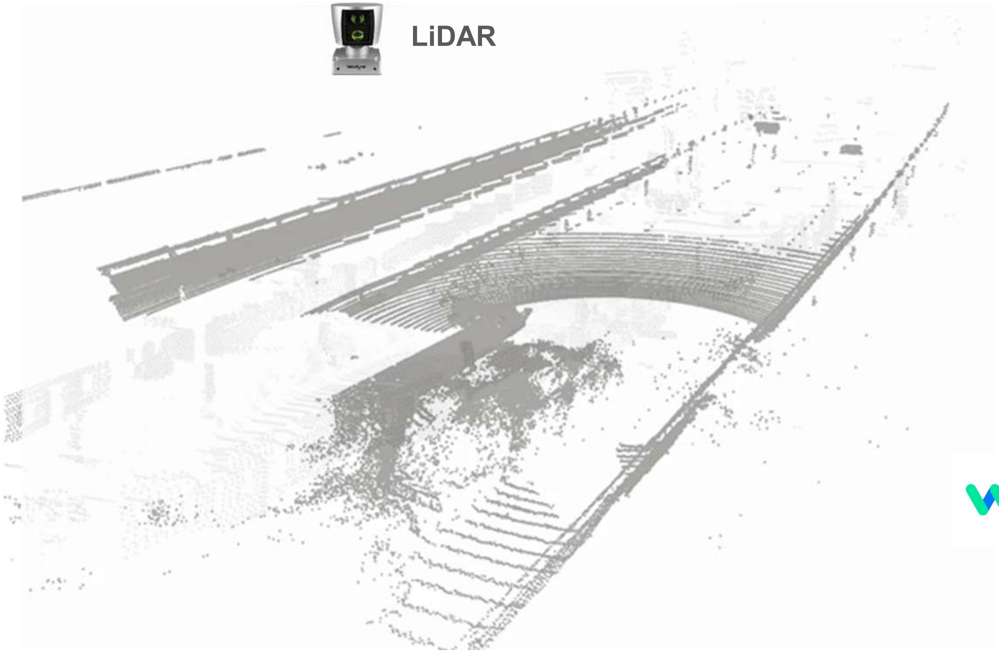
The Impact of Adverse Weather Conditions on Autonomous Vehicles

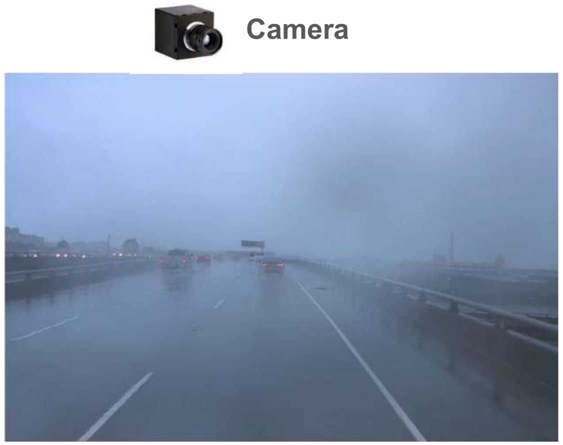
The **challenges** start with **harsh weather conditions**, such as **fog, rain, and snow**, which substantial affect the functioning of the key perception technologies and their development.

The Impact of Adverse Weather Conditions on Autonomous Vehicles

The **challenges** start with **harsh weather conditions**, such as **fog, rain, and snow**, which substantial affect the functioning of the key perception technologies and their development.

Both sensors are negatively impacted by adverse weather conditions!





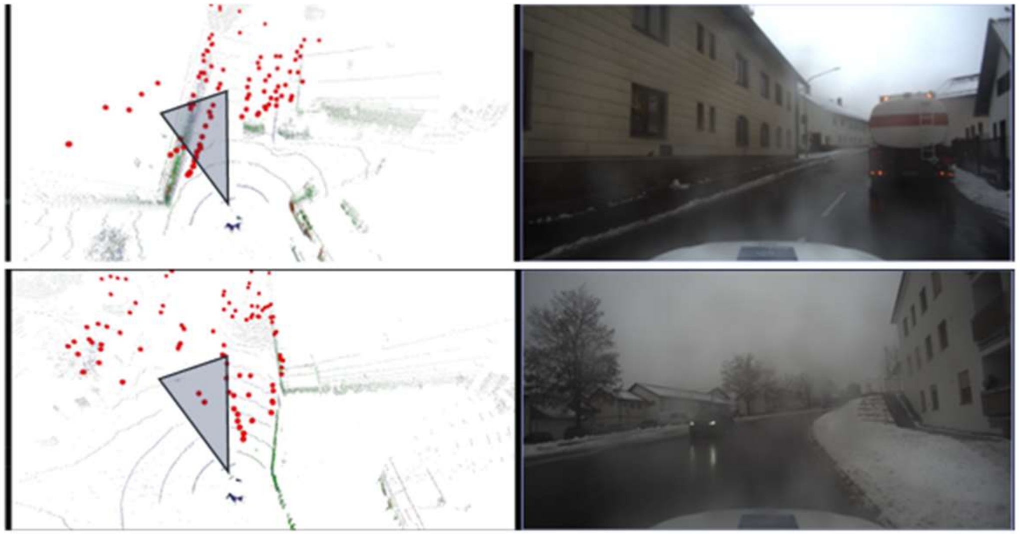
WAYMO

Sensor Contamination in Real-time

- Evaluation of sensors in-situ

Contamination due to wet, sticky snow.

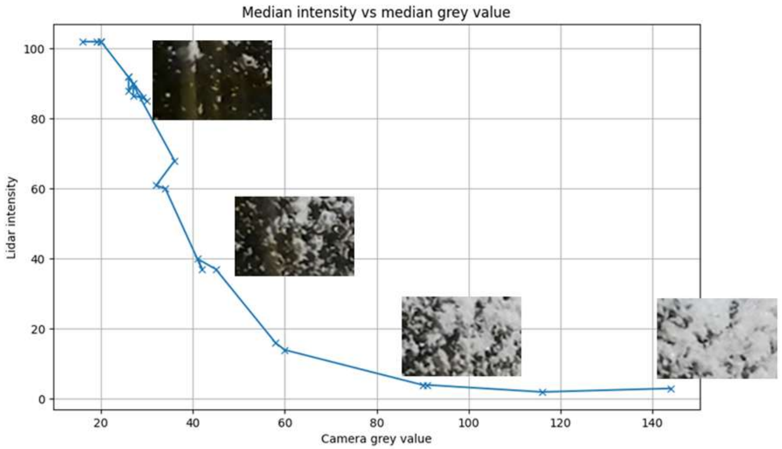
Rapid degradation of sensor performance.

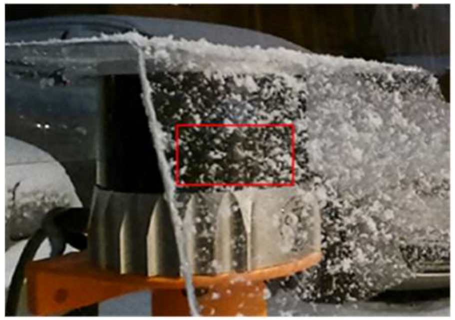


The time difference between the upper and the lower row **is 8.5 seconds**. The left column shows lidar point cloud (grey) and radar point cloud (red). The difference is also noticeable in the front looking camera.

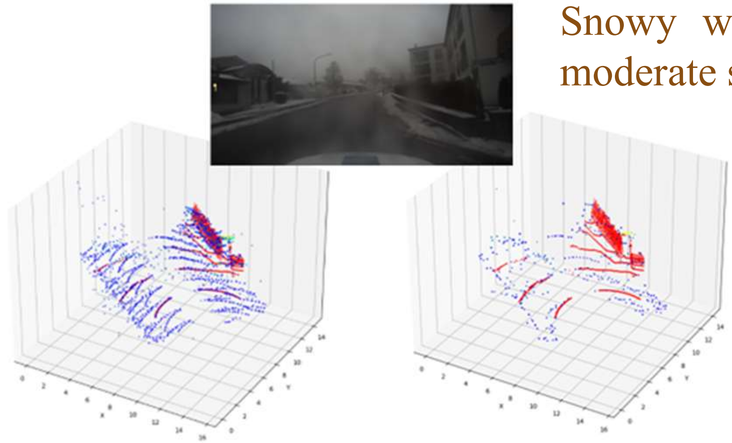
Sensor Contamination in Real-time

- Evaluation of sensors in-situ

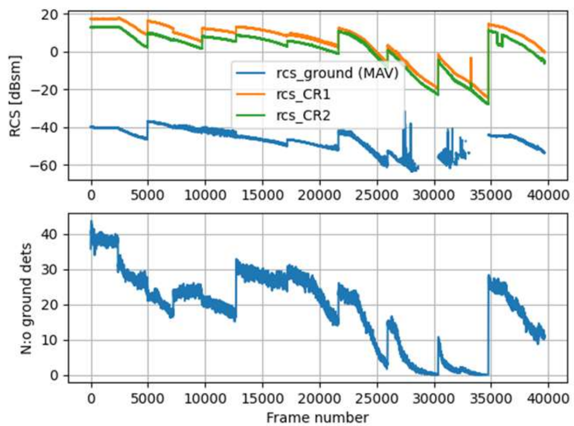




Snow on a flat shield. The red box is the area used to estimate the coverage of snow.



Snowy weather, wet ground, moderate speed, contaminated.



The radar is also degraded, but more gradually!

Lack of Datasets for Snowy Conditions

No Snow! (KITTI, Waymo)

Dataset	Year	Modality				3D Annotation			#Frames	#Classes	Snow
		LiDAR	RGB	Thermal	GNSS/IMU	BB	SL	SF			
KITTI [15]	2012	64	90°	-	✓/✓	✓	-	-	15K	8	-
KAIST [10]	2018	32	26°	25°	✓/✓	✓	-	-	95K	3	-
nuScenes [7]	2019	32	360°	-	✓/✓	✓	✓	-	40K	23	-
Waymo [29]	2020	64*	360°	-	✓/✓	✓	✓	-	230K	4	-
A2D2 [16]	2020	16	360°	-	✓/✓	✓	-	-	12K	14	-
Argoverse 2 [34]	2021	32	360°	-	- / -	✓	-	-	150K	30	-
SemanticKITTI [4]	2021	64	-	-	✓/✓	-	✓	-	43K	28	-
CADC [22] (Single-task)	2021	32	360°	-	✓/✓	✓	-	-	7K	10	✓
WADS [20] (Unimodal)	2021	64	-	-	-	-	✓	✓	2K	22	✓
Ithaca365 [13] (800 Frames)	2022	128	60°	-	✓/✓	✓	-	-	7K	6	✓
Boreas [6]	2023	128	81°	-	✓/✓	✓	-	-	7K	3	✓
ZOD [1]	2023	128	120°	-	✓/✓	✓	-	-	100K	29	✓
SemanticSTF [36] (700 Frames)	2023	64	-	-	-	-	✓	-	2K	21	✓
MSU-4S [19]	2024	64	150°	-	✓/✓	✓	-	-	100K	3	✓
MAN TruckScenes [14]	2024	64	360°	-	✓/✓	✓	-	-	30K	27	✓

* For the top spinning LiDAR.

Current datasets offer **limited annotated data** for harsh weather conditions, suffer from **low modality diversity**, and typically cover **only a single perception task!**

ROADVIEW

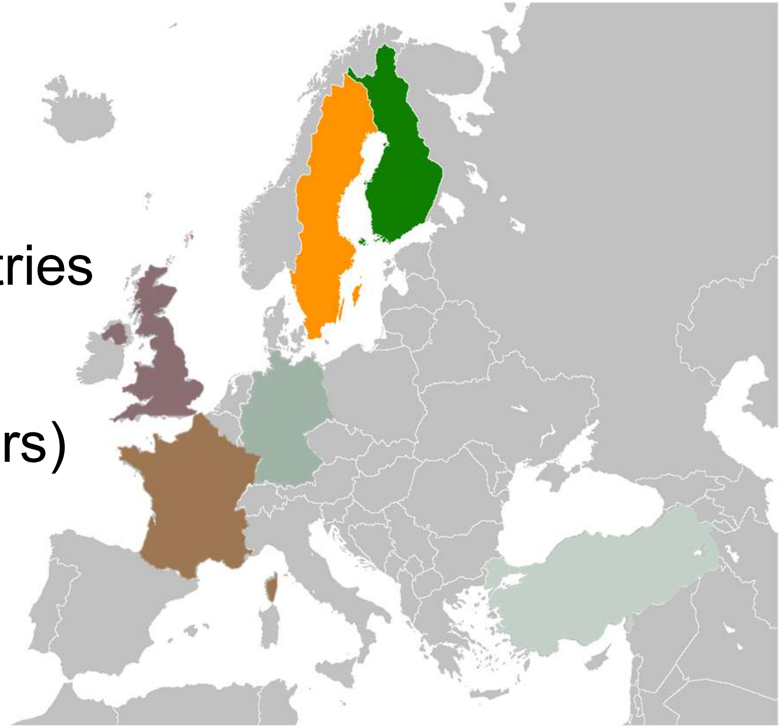
Robust Automated Driving in Extreme Weather

15 partners

7 European countries

2022-2026 (4 years)

9.7M€



NLS FINNISH GEOSPATIAL RESEARCH INSTITUTE FGI

AVL

VTT

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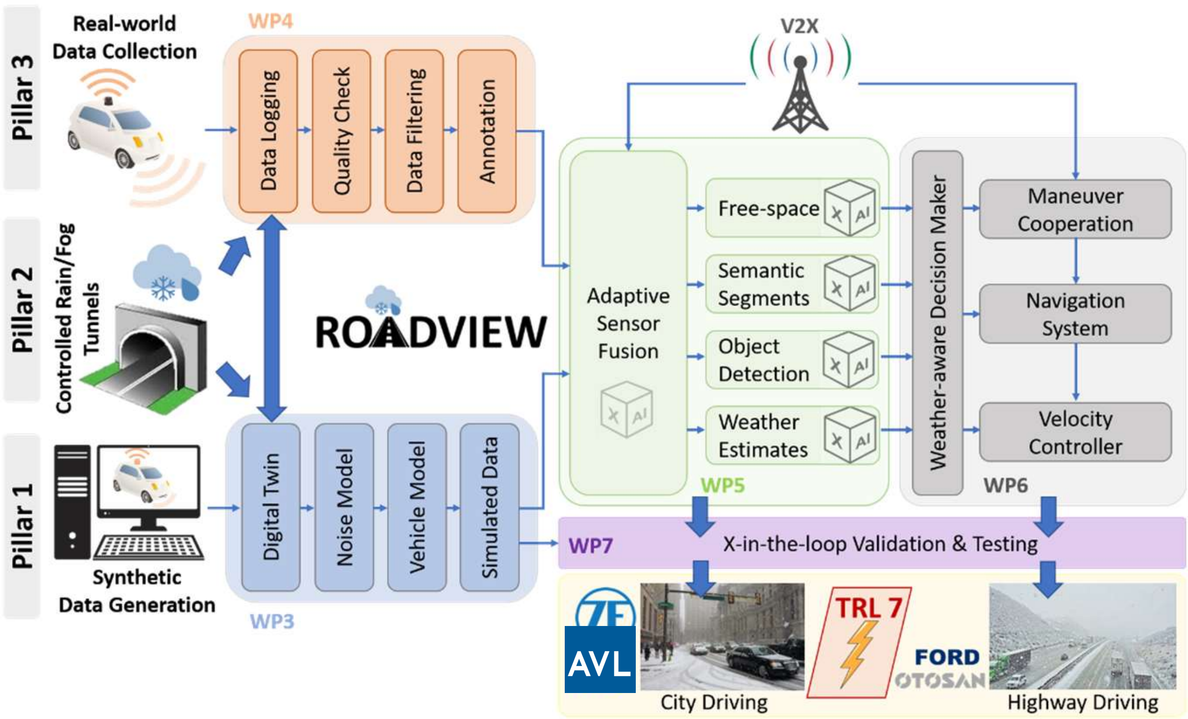
ROADVIEW: Objective & Methodology

ROADVIEW addresses these *weather-related challenges* by developing *robust and cost-efficient embedded in-vehicle perception* and *weather-aware decision-making systems* for *connected and automated vehicles* with enhanced performance *under harsh weather conditions.*

ROADVIEW involves ***three main pillars!***



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Pillar 1: Synthetic Data Generation

Simulator

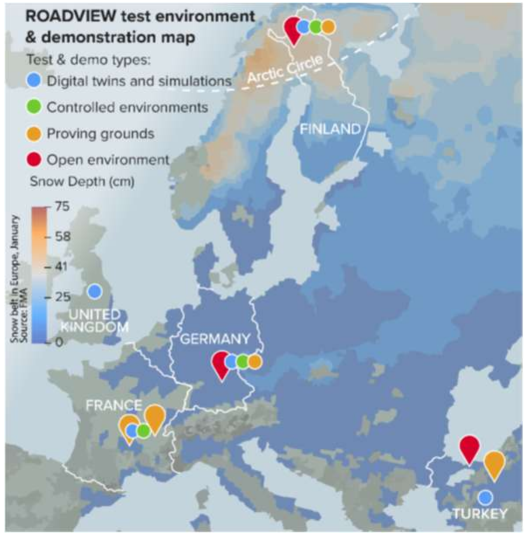
WinterSIM CARLA LAPIN AMK Lapland University of Applied Sciences

Click Here to Watch Video
YouTube

Digital Twins

LPG LAPLAND PROVING GROUND CARISSMA Technische Hochschule Ingolstadt LAPIN AMK Lapland University of Applied Sciences

ROADVIEW Test Locations



Real image (original)

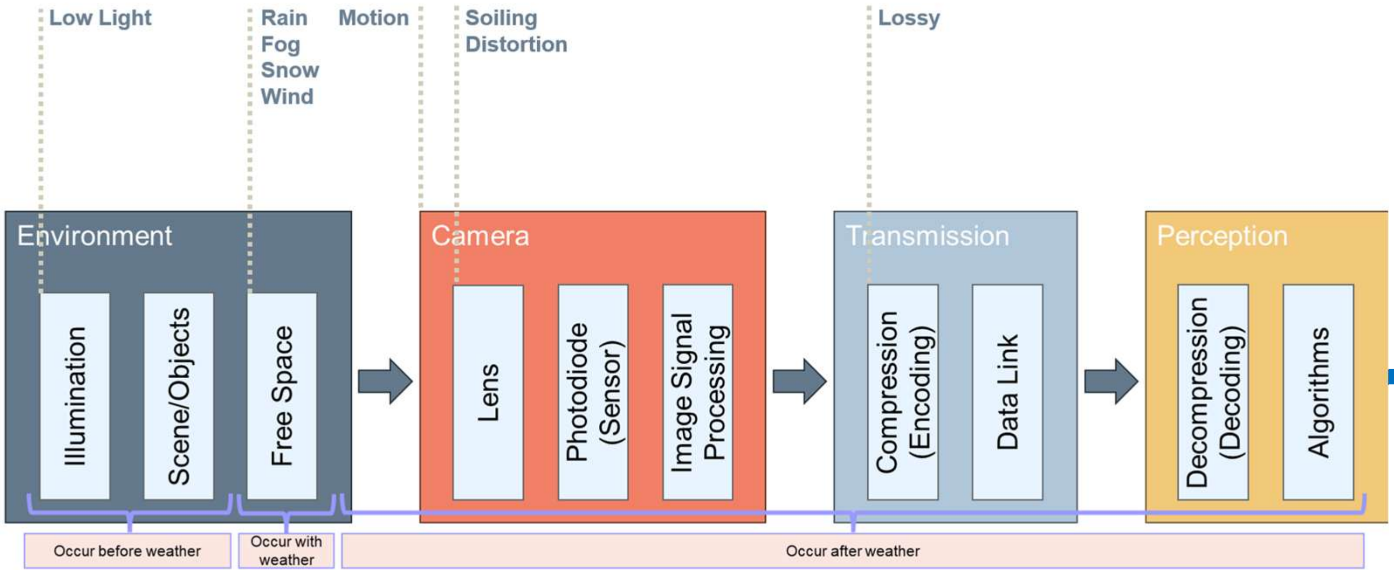
Snow simulation

Fog conditions

Generative AI Models

Pillar 1: Synthetic Data Generation

Compounding Methodology for Camera



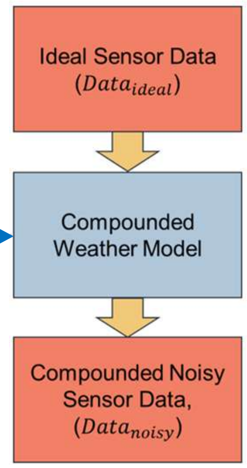
Camera Noise Model

- Intensity per pixel per colour channel:

$$I_{Noise} = (1-\tau)\cdot I_{ideal} + \tau \cdot I_{X\_noise}$$

- Rain: $I_{Rain\_noise} = 0.94 \cdot I_{FoV} + 0.06 \cdot luminosity$
- Fog: $I_{Fog\_noise} = transmission \cdot I_{ideal} + (1 - transmission) \cdot luminosity$
- Snow (initial): $I_{Snow\_noise} = reflectivity \cdot luminosity$
- τ, relative time on pixel:

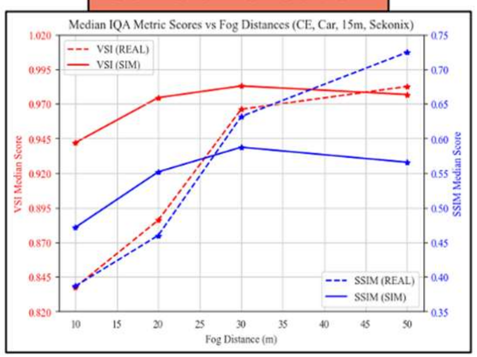
$$\tau = min\left\{\frac{1 + DropSize_{pix}}{v\_drop_{pix} * \epsilon}, 1\right\}$$



$$\left\{ \begin{array}{ll} Data_{noisy} = f_{weather}\left(\left(f_{noise}(Data_{ideal})\right)\right) & (1) \\ Data_{noisy} = f_{weather\cdot noise}(Data_{ideal}) & (2) \\ Data_{noisy} = f_{noise}\left(\left(f_{weather}(Data_{ideal})\right)\right) & (3) \end{array} \right.$$

$\left\{ \begin{array}{l} Carla \\ Carmaker \\ Dataset \\ Perception\ Sensor \end{array} \right.$

Camera Validation



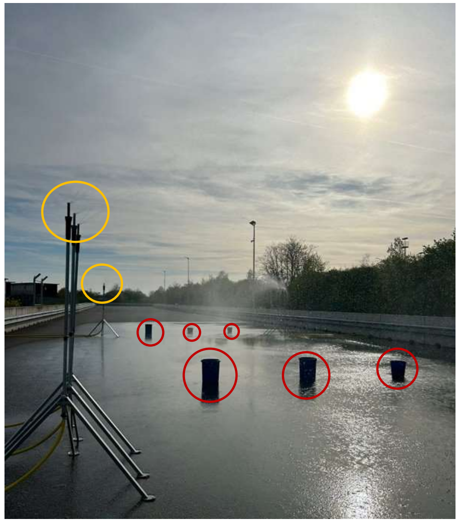
Pillar 1: Synthetic Data Generation

Compounding Methodology for Camera: Results

Pillar 2: Controlled Rain/Fog Tunnels

CARISSMA Technische Hochschule Ingolstadt

Outdoor Rain Simulation Facility



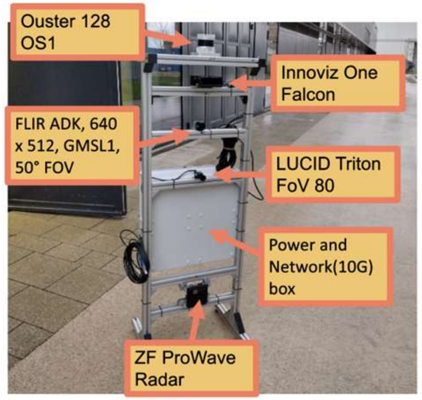
Rain Measurement Tools

- Sprinklers
- Buckets
- Disdrometer (rain)
- Anemometer (wind)

Sensor Setup

- Automotive grade
- RGB Camera
- Thermal Camera
- LiDAR (Innoviz One)
- 4D Radar

Validation of the best sensor suit!



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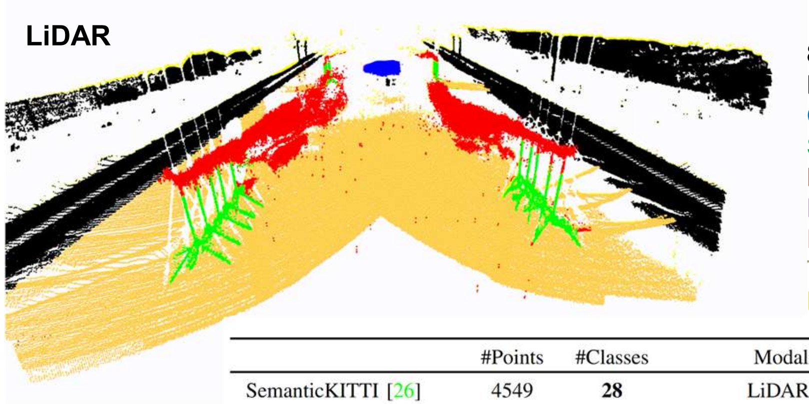
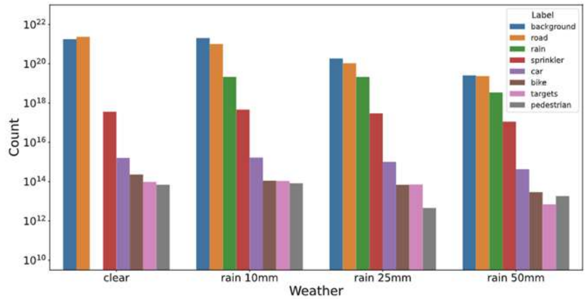
Pillar 2: Controlled Rain/Fog Tunnels

CARISSMA Technische Hochschule Ingolstadt

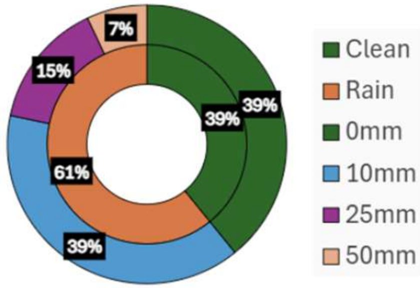
Outdoor Rain Simulation Facility



8 Classes:
Background,
Car,
Sprinkler,
Rain,
Pedestrian,
Biker,
Targets,
Road.



Number of Annotated Points



REHEARSE Data Distribution

GitHub
https://sporsho.github.io/REHEARSE3D

	#Points	#Classes	Modality	Annotation	Sequential	Weather	Rain Characteristics	Day/Night	Environment
SemanticKITTI [26]	4549	**28**	LiDAR-64	Point-wise	✓	Clean	-	-	Real
SnowyKITTI [27]	3940	2	LiDAR-64	Point-wise	✓	Snow	-	-	Simulated
WADS [8]	387	22	LiDAR-64	Point-wise	✓	Snow	-	-	Real
SemanticSpray [5]	526	3	LiDAR-32	Point-wise	✓	Rain	-	-	Real
WeatherNet [6]	1700	3	LiDAR-32	Point-wise	✓	Rain/Fog	✓	-	Real
REHEARSE-3D (Ours)	**9200**	8	LiDAR-**256*** & 4D-Radar	Point-wise	✓	Rain/Clean	✓	✓	Real

* The LiDAR is a MEMS LiDAR with 256 lines.

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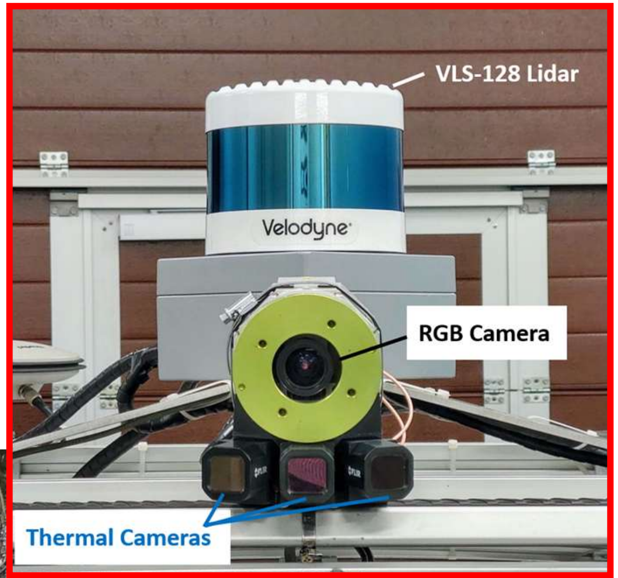
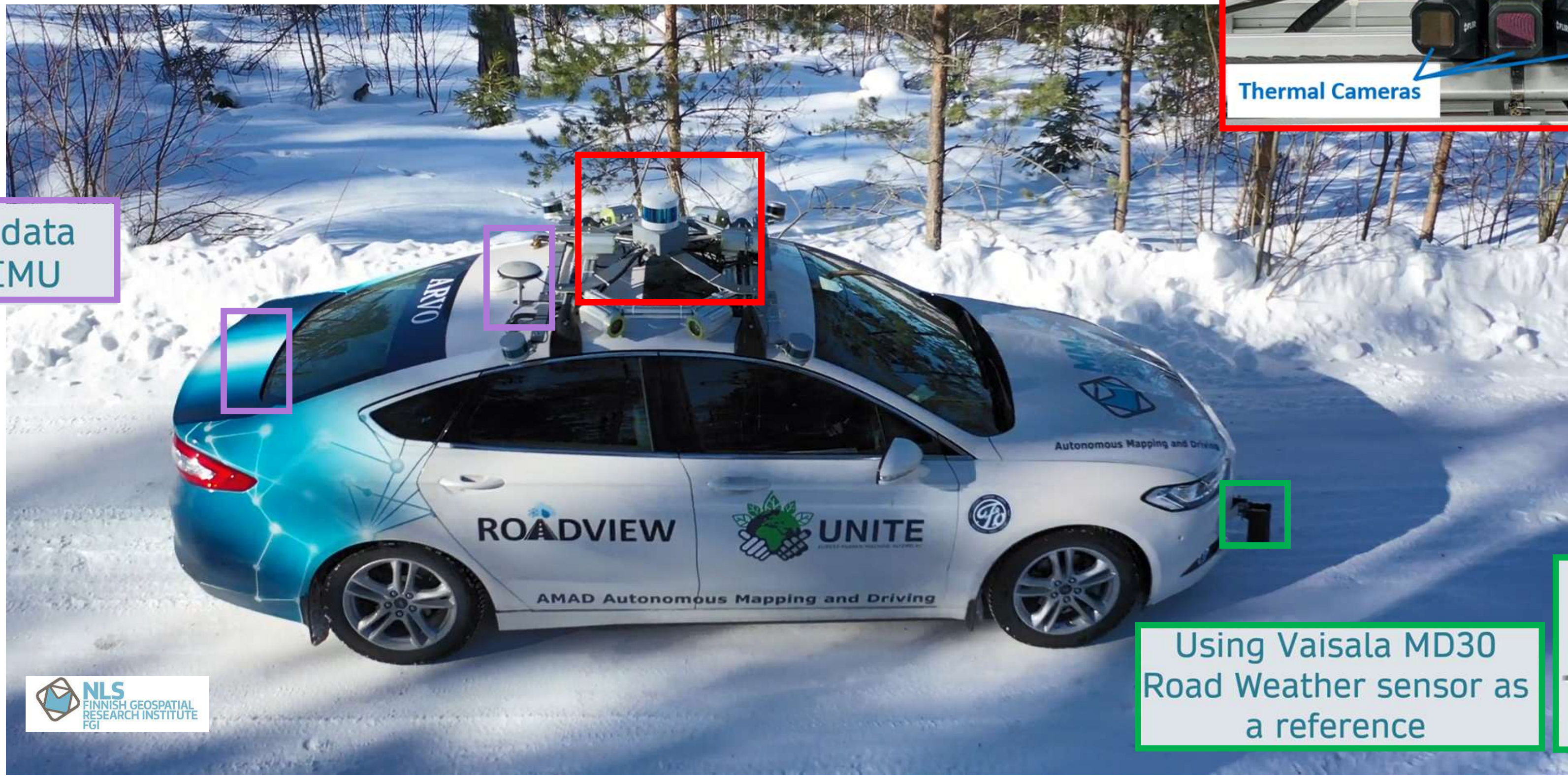
Pillar 3: Real World Data

NLS FINNISH GEOSPATIAL RESEARCH INSTITUTE FGI **Sensor Fusion**

- RGB Camera (Basler acA1920-155um),
- 3 Thermal Cameras (Flir ADK 640x512), and
- LiDAR (Velodyne VLS-128)

- All sensors hardware time-synchronized



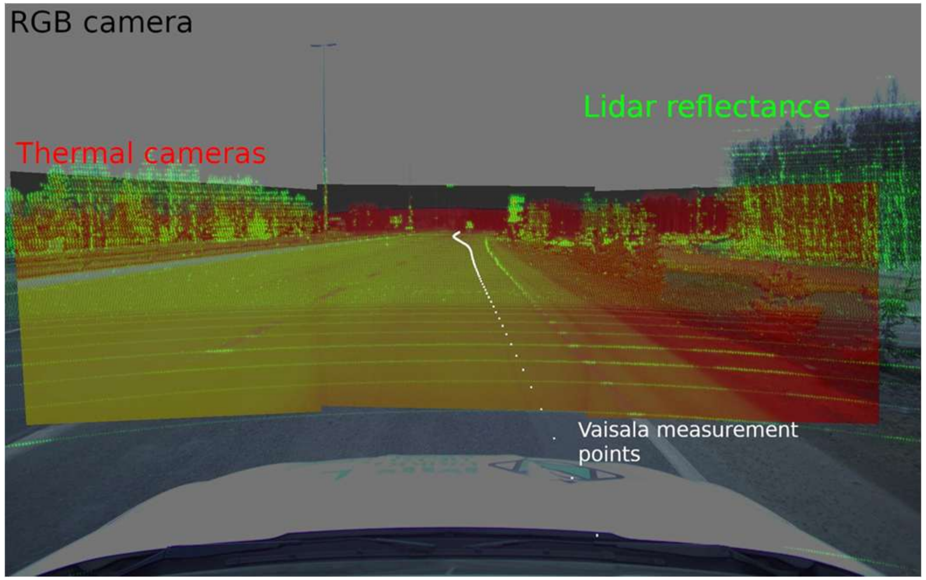


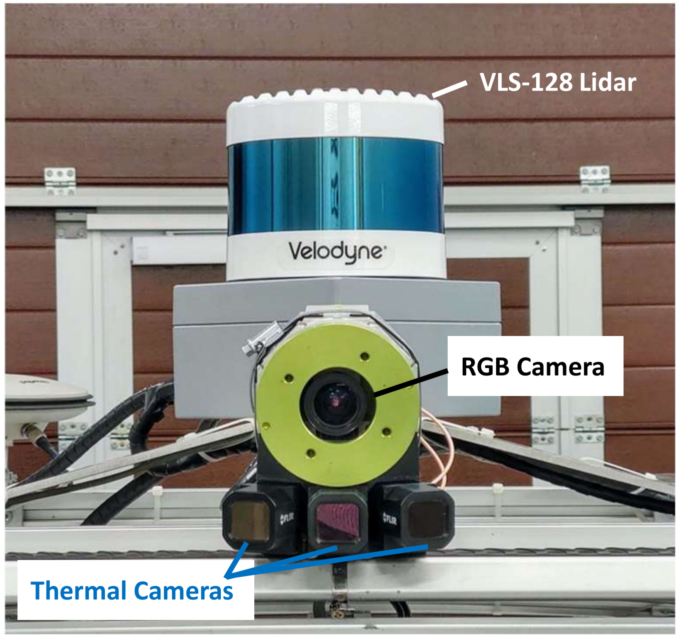
Georeferencing data using GNSS + IMU

Using Vaisala MD30 Road Weather sensor as a reference

Pillar 3: Real World Data: Sensor Fusion

Sensor Fusion for the Slipperiness Prediction





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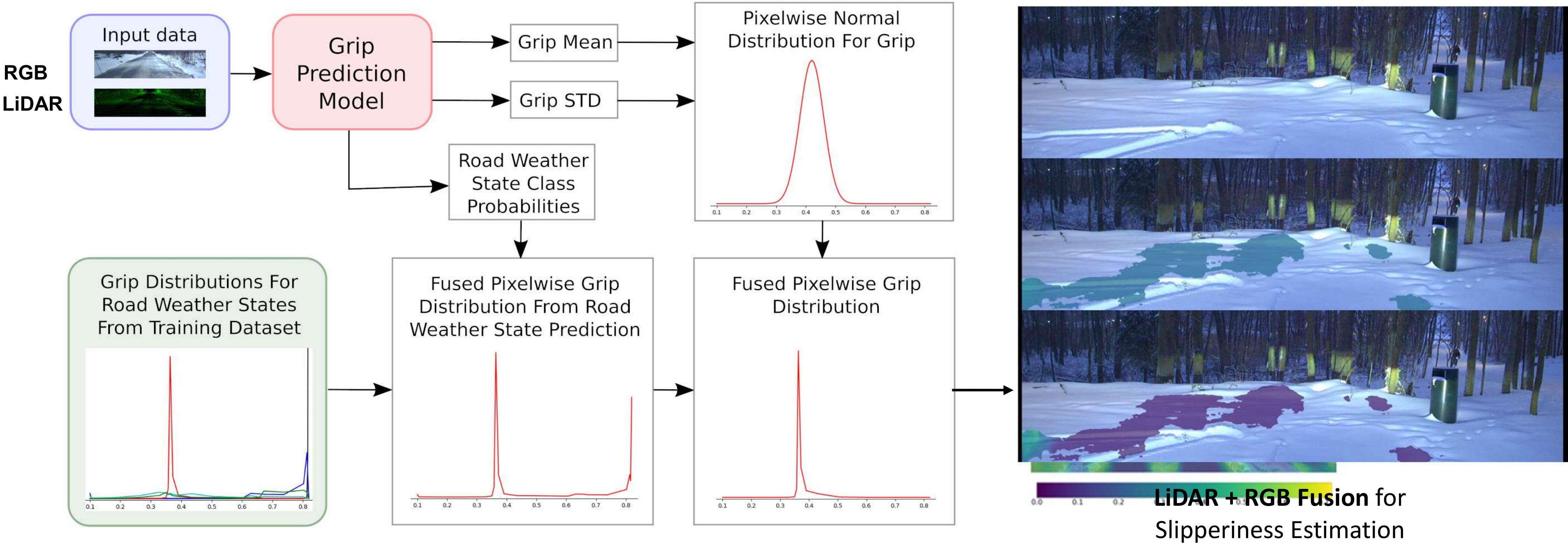
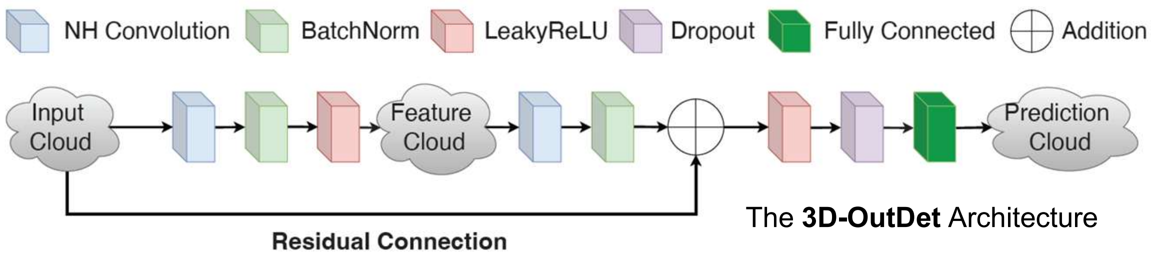
Pillar 3: Real World Data: Sensor Fusion

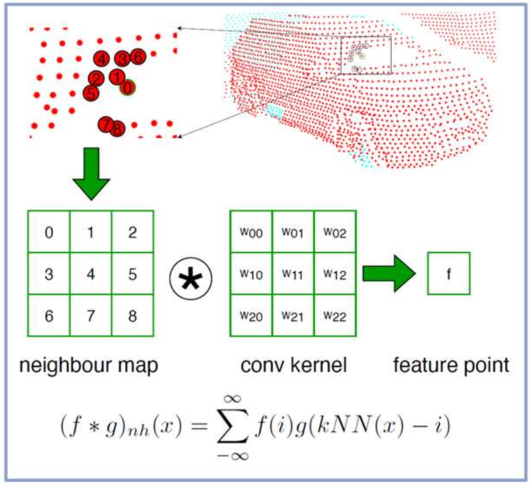
Sensor Fusion for the Slipperiness Prediction with Uncertainty Distribution



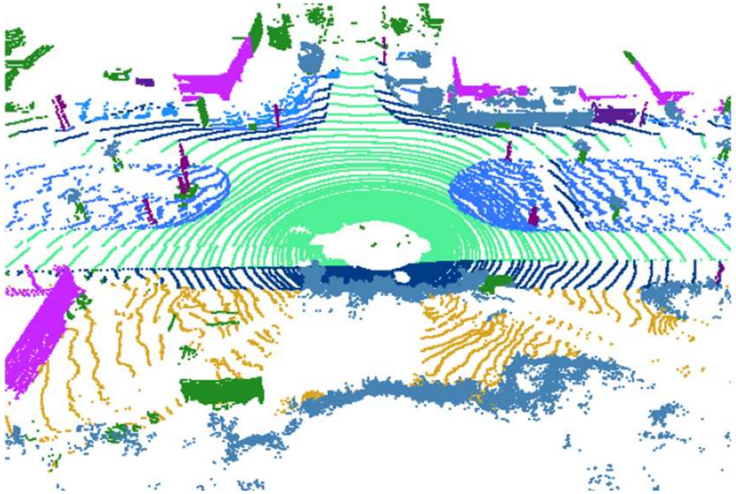
Pillar 3: Real World Data: Filtering

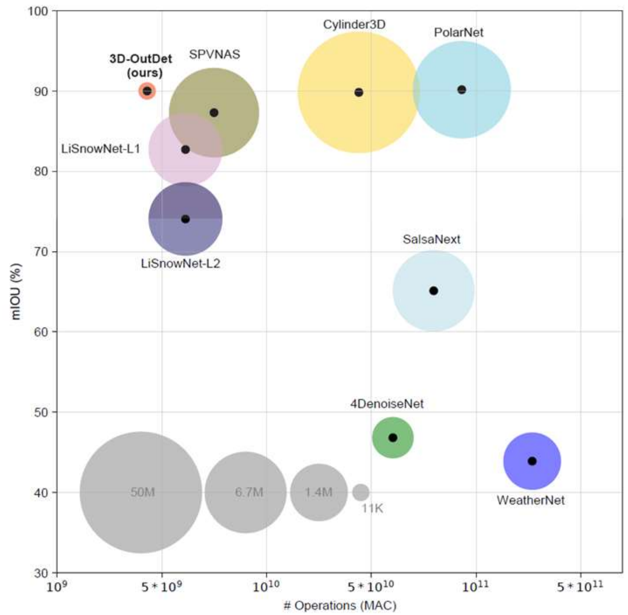


The **3D-OutDet** Architecture

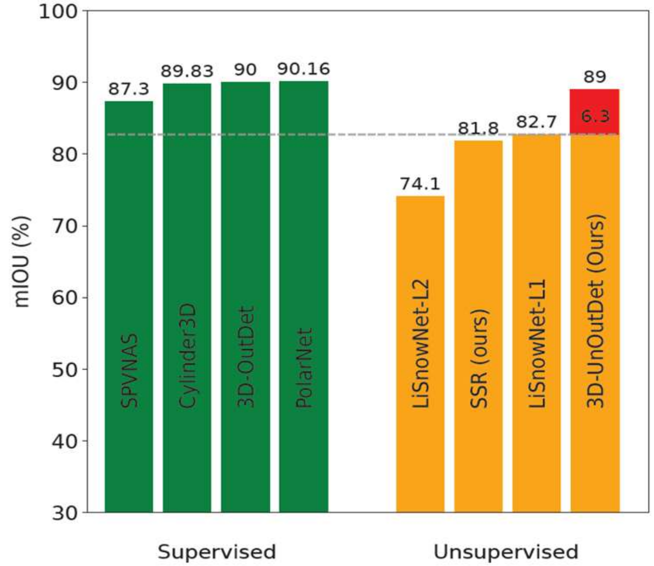


The concept of **NH Convolution**



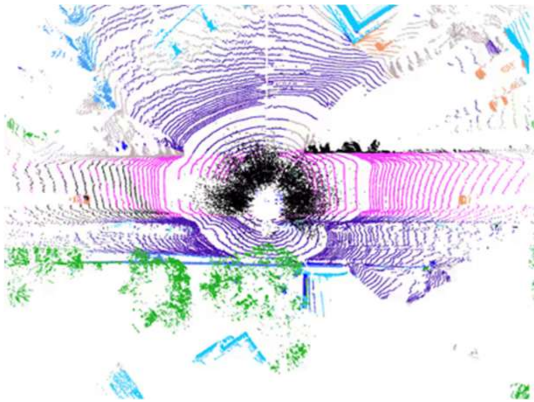


Existing SoA filtering methods suffer in real-time applications due to **large memory consumption** and **long execution times.**

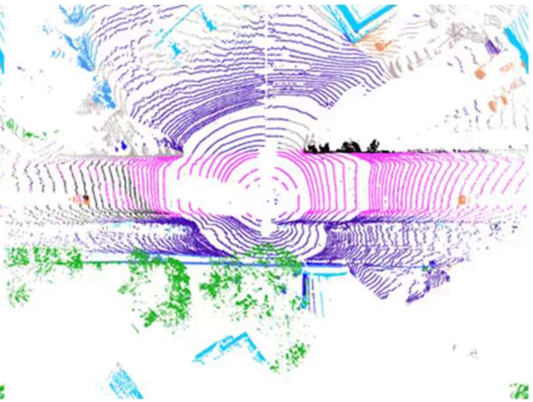


Raisuddin A. et al., "3D-OutDet" in IROS 2025

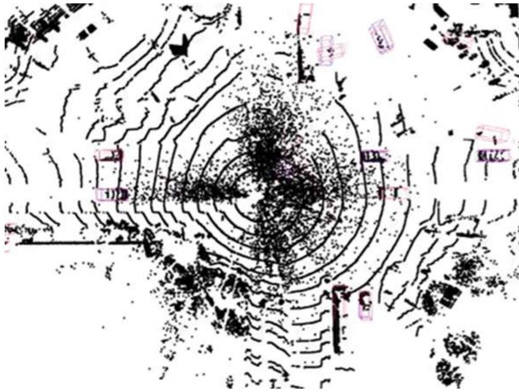
Pillar 3: Real World Data: Filtering



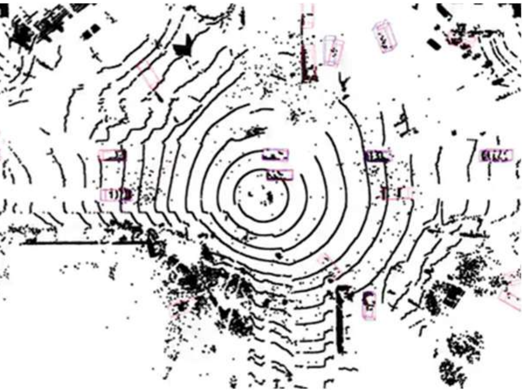
Snowy Point Cloud
from the WADS Dataset



Filtered Clean Point Cloud using
3D-UnOutDet



Snowy Point Cloud
from the CADC Dataset



Filtered Clean Point Cloud using
3D-UnOutDet

Multi-class Semantic Segmentation Performance after the snow removal on WADS

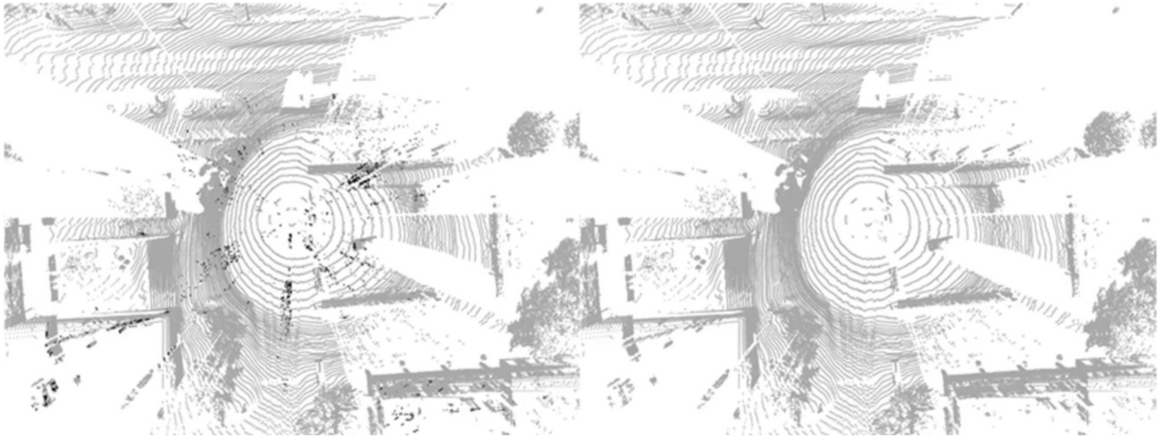
	car	truck	other-vehicle	person	road	parking	sidewalk	other-ground	building	fence	other-structure	vegetation	trunk	terrain	pole	traffic-sign	other-object	accum snow	mIOU
Cylinder3D [10]	46.88	0.22	0.05	21.32	58.39	12.20	20.14	2.37	63.21	26.25	1.40	52.87	0.00	0.02	28.09	16.61	4.09	48.90	22.39
Cylinder3D [10] + 3D-UnOutDet	66.10	0.04	0.00	50.66	62.68	10.93	30.03	4.78	64.77	30.82	1.78	62.68	0.00	0.00	31.06	23.91	3.95	52.99	27.62
Δ_2	+19.22	-0.18	-0.05	+29.34	+4.29	-1.27	+9.89	+2.41	+1.56	+4.57	+0.38	+9.81	0.00	-0.02	+2.97	+7.30	-0.14	+5.09	+5.23

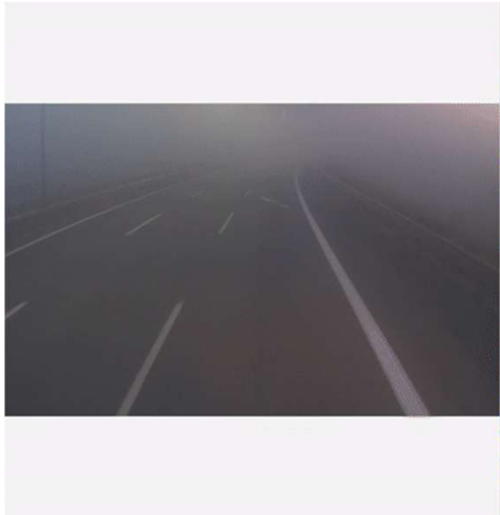
Object [car] Detection Performance on CADC.

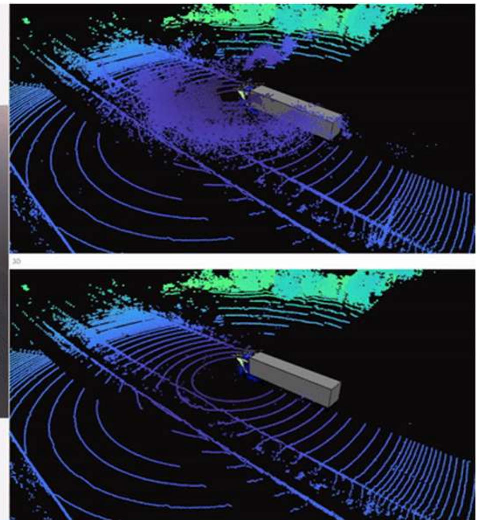
	Car mAP R40			
	Easy	Med	Hard	Avg
PointPillars [24]	63.95	51.97	45.27	53.73
PointPillars [24] + 3D-UnOutDet (ours)	65.57	54.37	47.39	55.77
Δ	+1.62	+2.40	+2.12	+2.04
CenterPoint [25]	57.61	51.86	45.41	51.63
CenterPoint [25] + 3D-UnOutDet (Ours)	58.24	52.94	46.37	52.52
Δ	+0.63	+1.08	+0.96	+0.89
SECOND [26]	67.63	55.15	48.27	57.02
SECOND [26] + 3D-UnOutDet (ours)	67.80	57.60	50.58	58.66
Δ	+0.17	+2.45	+2.31	+1.64

GitHub https://sporsho.github.io/3DOutDet

Pillar 3: Real World Data: Filtering







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Filtering Snowy Point Clouds
logged in Finland

Filtering Rainy Point Clouds
logged in Turkey

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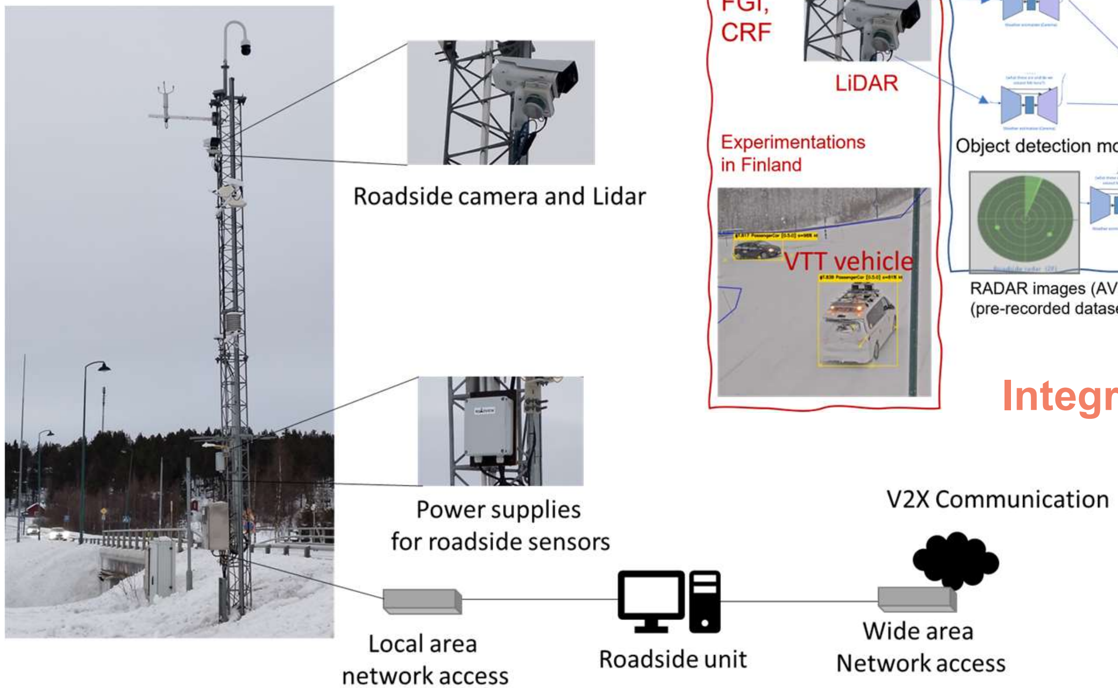
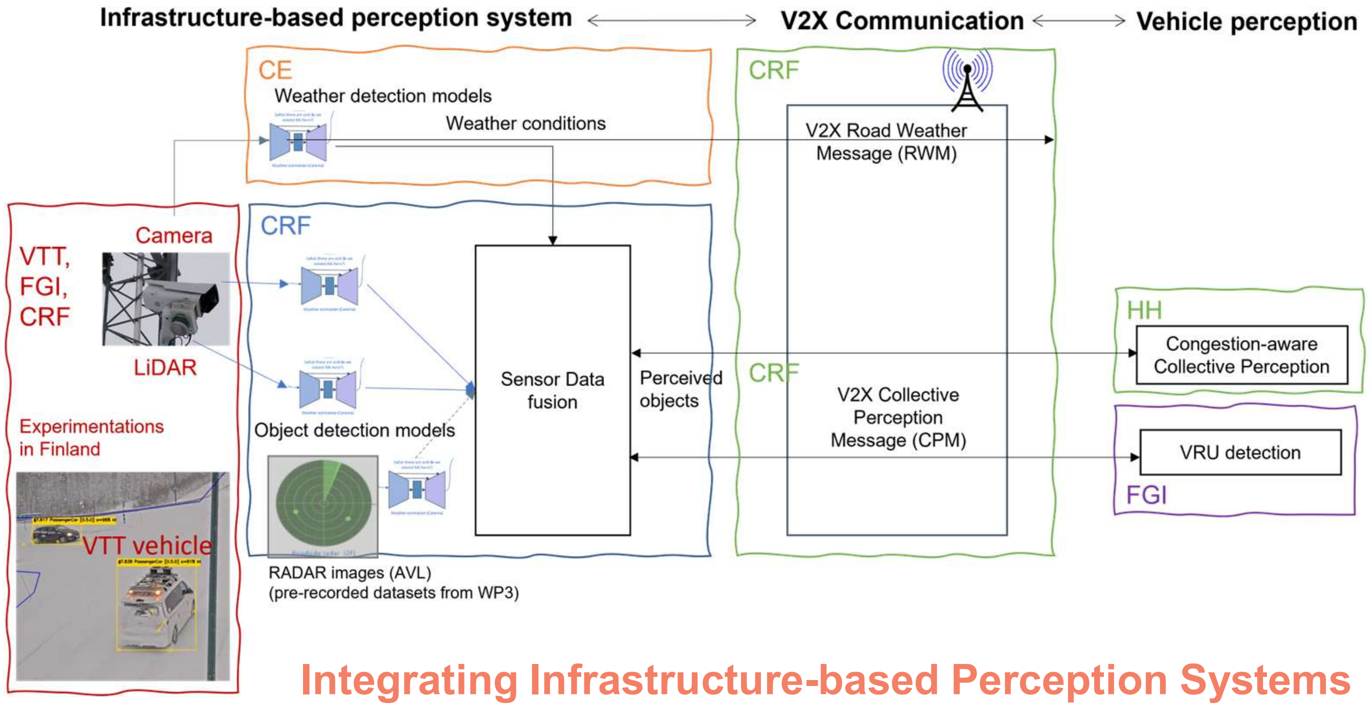
Pillar 3: Real World: Collaborative Perception

Data collection in Finland

Minimum recorded temperature during the tests: - 34 °C





Integrating Infrastructure-based Perception Systems

Pillar 3: Real World: Collaborative Perception

RGB + LiDAR Fusion for Collaborative Perception via V2X (vehicle detection & semantic segmentation)

Daytime

Nighttime

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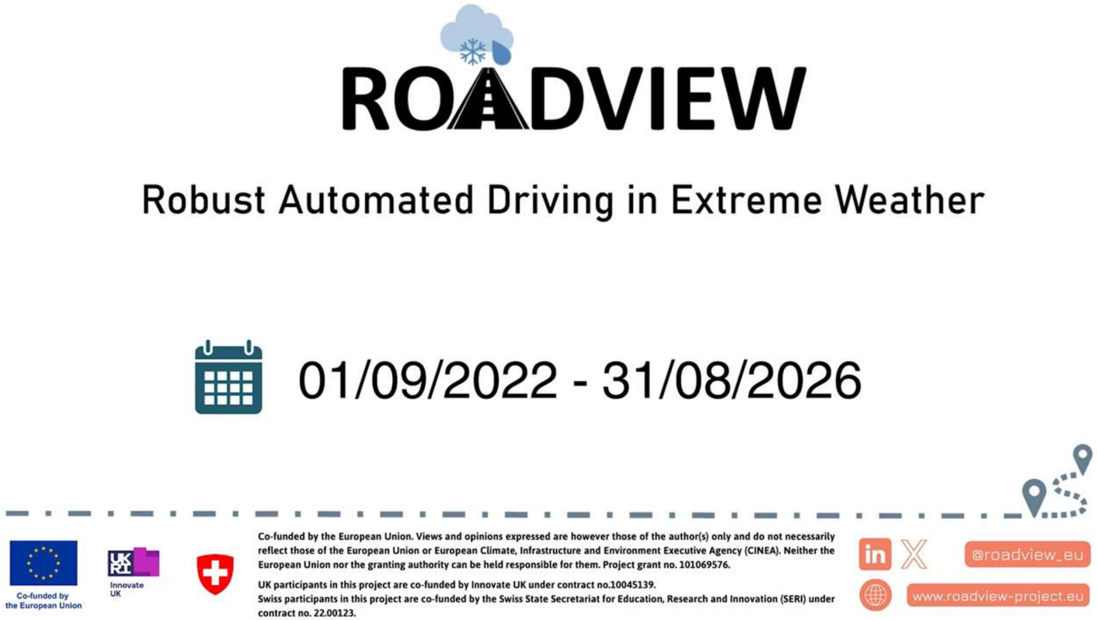
Pillar 3: Real World: Vehicle Control

VTT

- **Weather Conditional Navigation system and Velocity Controller**
  - The onboard weather decision maker uses AI-based slipperiness and visibility data to monitor ODD limits and trigger a safe stop (MRM) if limits are exceeded. MRM follows ISO 23793-1:2024!



The MRM fallback function is triggered via V2X communication (from the infrastructure) to safely pull over to the road shoulder.

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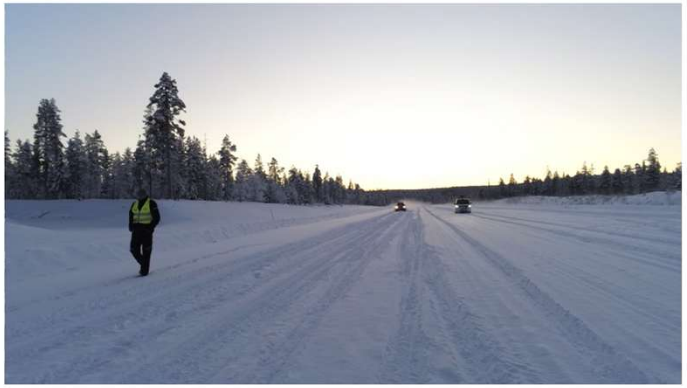
Pillar 3: Real World: Vehicle Control

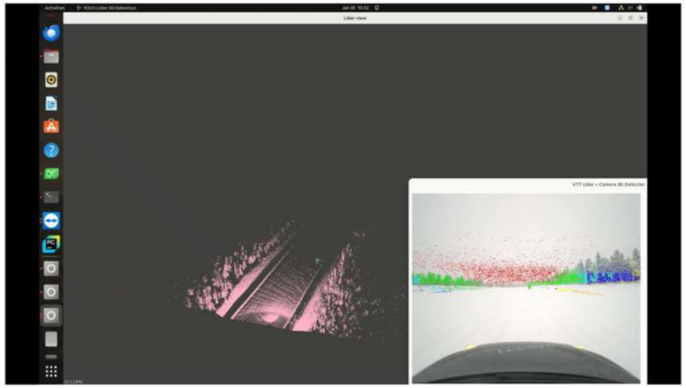
VTT

- **Weather Conditional Navigation system and Velocity Controller**
  - The onboard weather decision maker uses AI-based slipperiness and visibility data to monitor ODD limits and trigger a safe stop (MRM) if limits are exceeded. MRM follows ISO 23793-1:2024!

VTT measurements in LPG: C5

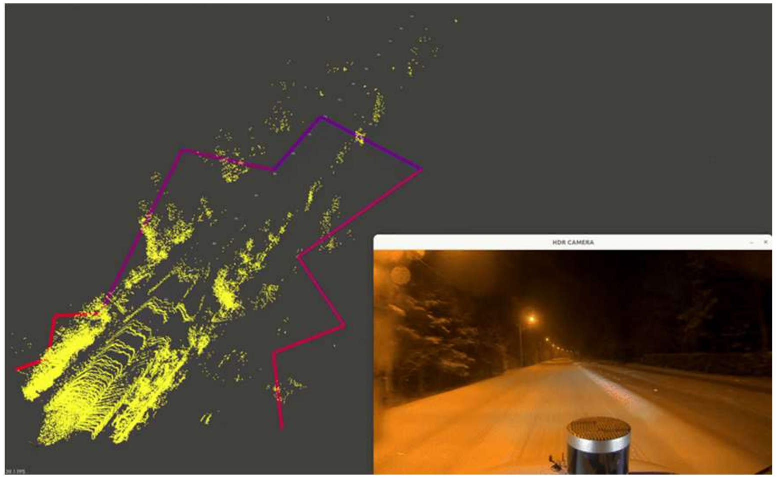
C 5	Friction needed to match the speed of another road user is taken into account by starting the deceleration early enough	Pedestrian walking along the lane to the same direction	UC3: interacting with VRU





The videos demonstrate the test scenario and conditions observed during the evaluation.
These videos were not captured from the same test drive.

ROADVIEW 1



LiDAR-based Online Visibility Estimator

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Pillar 3: Real World: Snowy Scenes

No Snow! (KITTI, Waymo)

Single-task (CADC)

Unimodal (WADS)

800 Frames (Ithaca365)

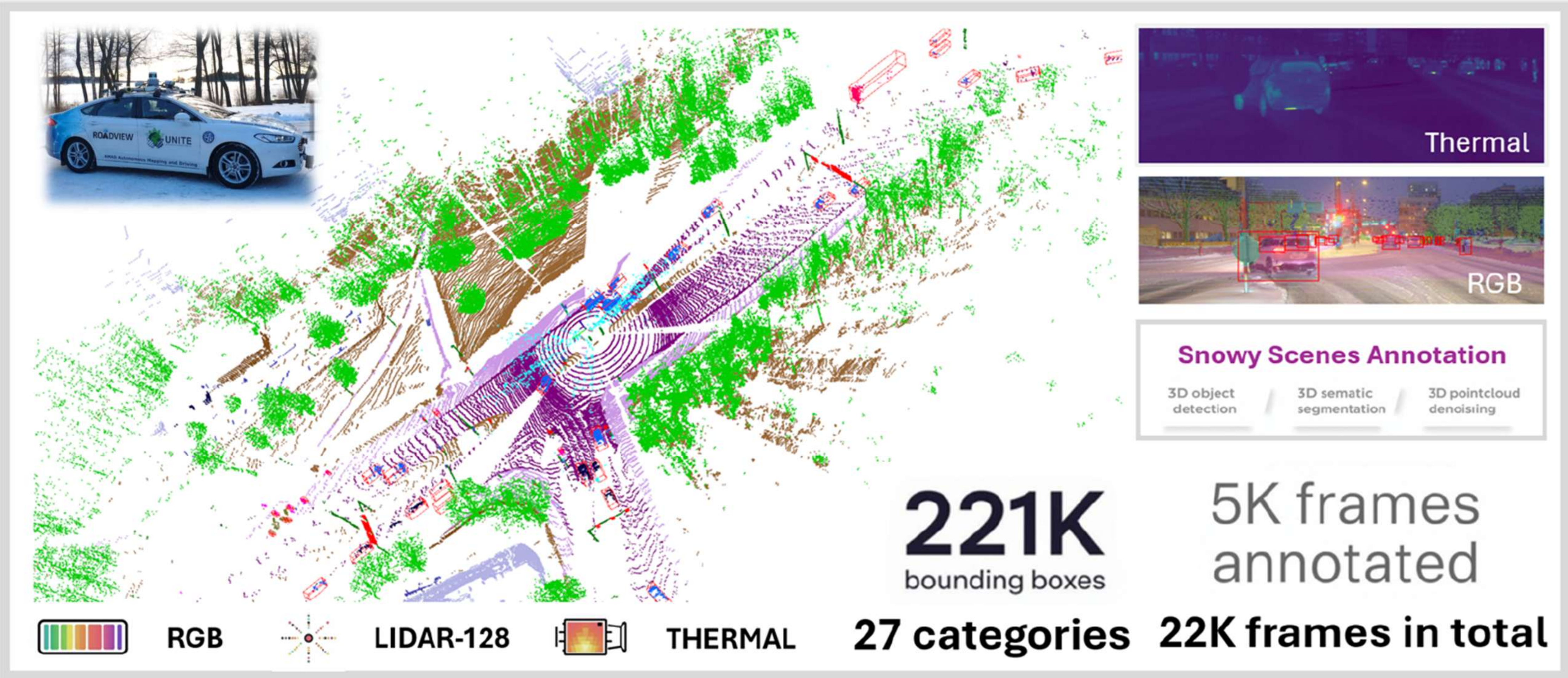
700 Frames (SemanticSTF)

		Modality				3D Annotation					
Dataset	**Year**	**LiDAR**	**RGB**	**Thermal**	**GNSS/IMU**	**BB**	**SL**	**SF**	**#Frames**	**#Classes**	**Snow**
KITTI [15]	2012	64	90°	-	✓/✓	✓	-	-	15K	8	-
KAIST [10]	2018	32	26°	25°	✓/✓	✓	-	-	95K	3	-
nuScenes [7]	2019	32	360°	-	✓/✓	✓	✓	-	40K	23	-
Waymo [29]	2020	64*	360°	-	✓/✓	✓	✓	-	230K	4	-
A2D2 [16]	2020	16	360°	-	✓/✓	✓	-	-	12K	14	-
Argoverse 2 [34]	2021	32	360°	-	- / -	✓	-	-	150K	30	-
SemanticKITTI [4]	2021	64	-	-	✓/✓	-	✓	-	43K	28	-
CADC [22]	2021	32	360°	-	✓/✓	✓	-	-	7K	10	✓
WADS [20]	2021	64	-	-	-	-	✓	✓	2K	22	✓
Ithaca365 [13]	2022	128	60°	-	✓/✓	✓	-	-	7K	6	✓
Boreas [6]	2023	128	81°	-	✓/✓	✓	-	-	7K	3	✓
ZOD [1]	2023	128	120°	-	✓/✓	✓	-	-	100K	29	✓
SemanticSTF [36]	2023	64	-	-	-	-	✓	-	2K	21	✓
MSU-4S [19]	2024	64	150°	-	✓/✓	✓	-	-	100K	3	✓
MAN TruckScenes [14]	2024	64	360°	-	✓/✓	✓	-	-	30K	27	✓
Snowy Scenes	2025	128	70°	72°**	✓/✓	✓	✓	✓	5K***	27	✓

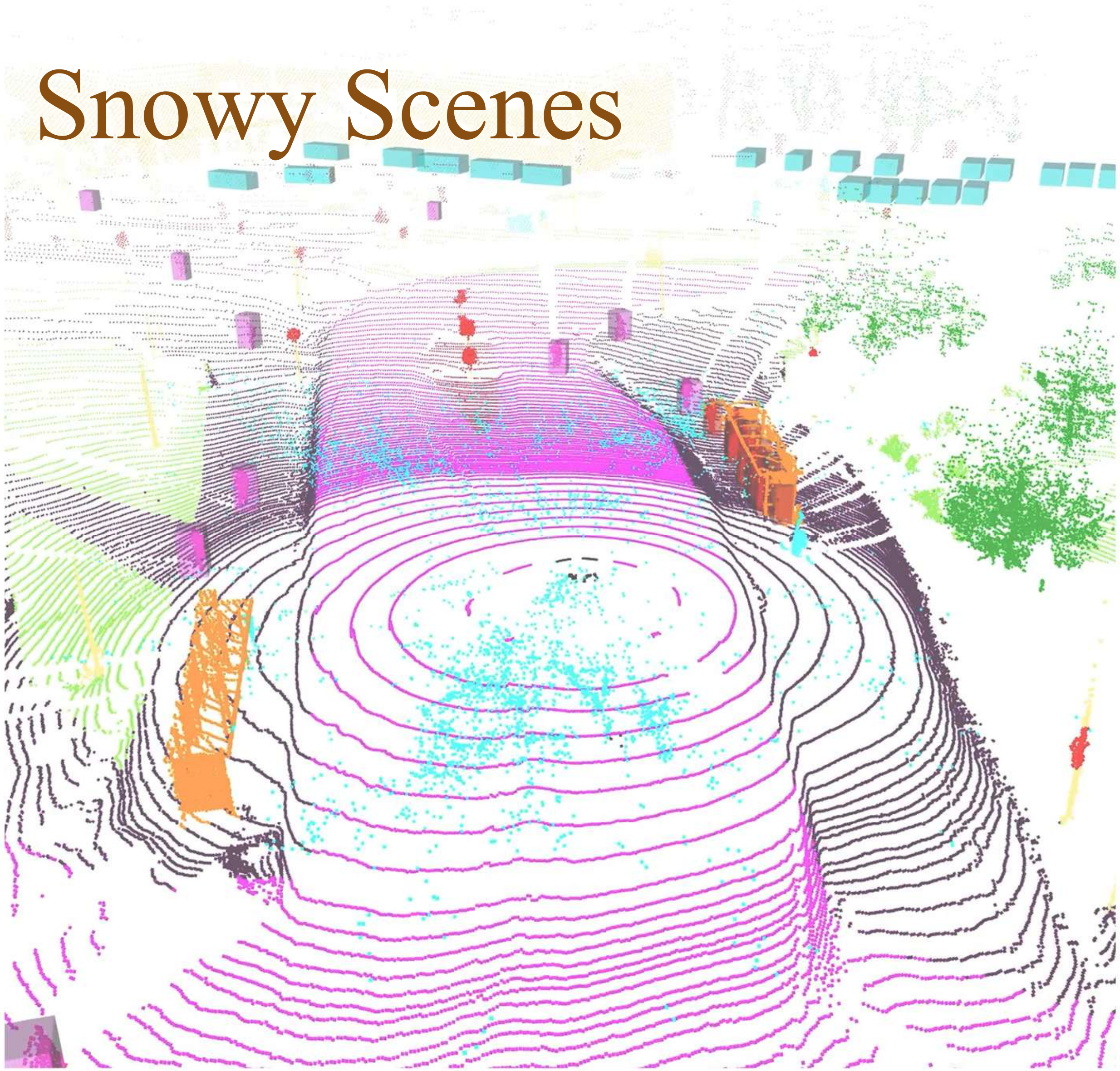
* For the top spinning LiDAR. ** Combined HFOV of 3 thermal cameras. *** Total amount of collected data is over 22K.

Current datasets offer **limited annotated data** for harsh weather conditions, suffer from **low modality diversity**, and typically cover **only a single perception task!**

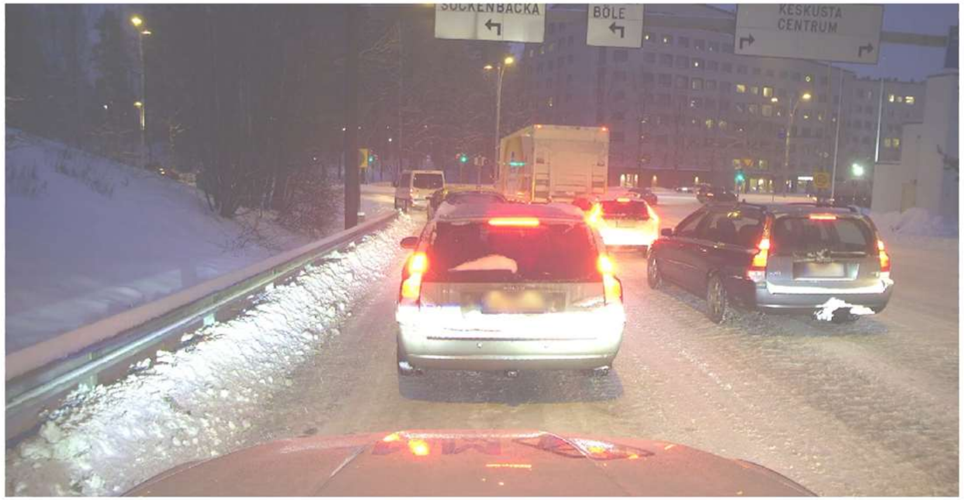
Pillar 3: Real World: Snowy Scenes

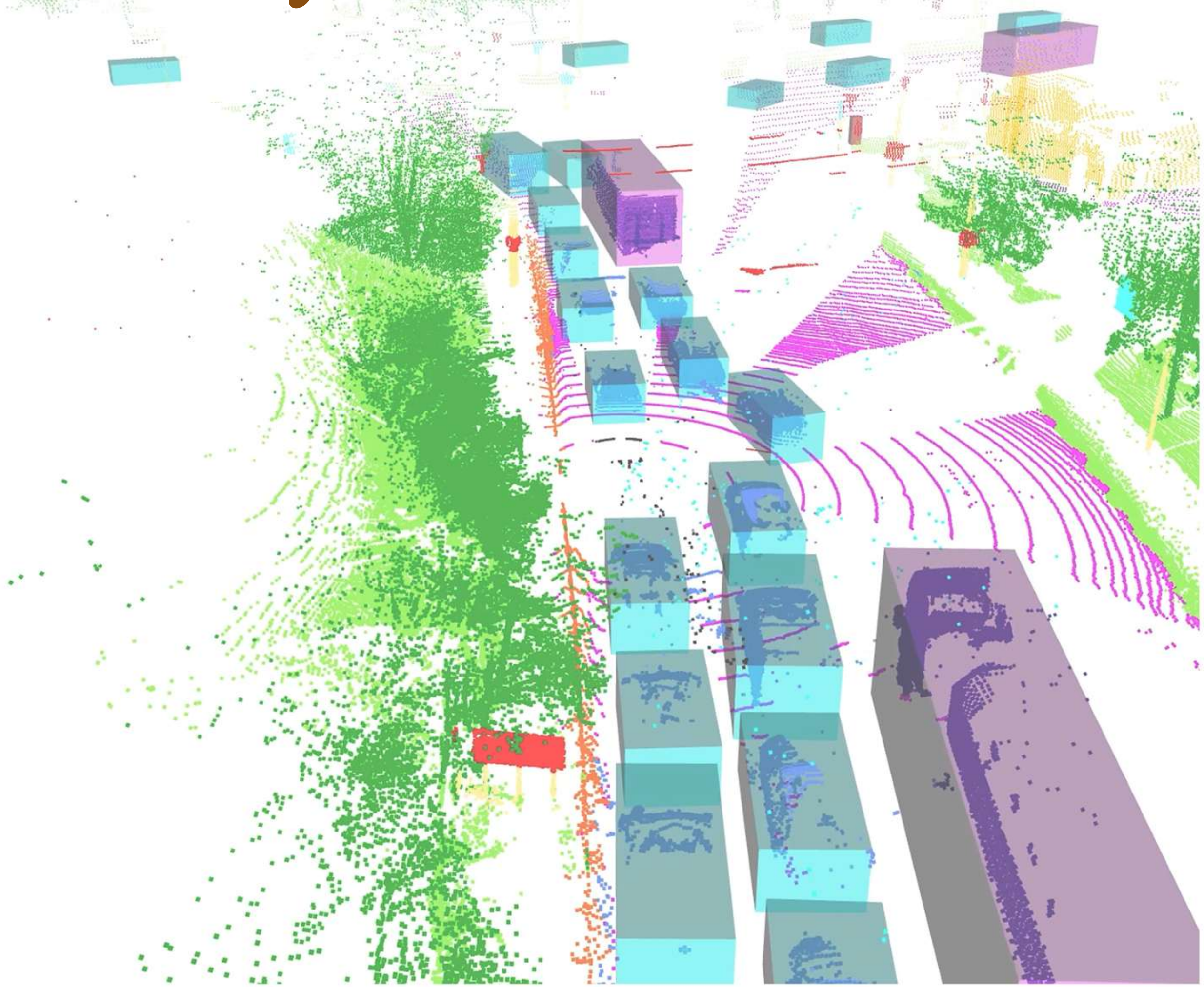


Pillar 3: Real World: Snowy Scenes



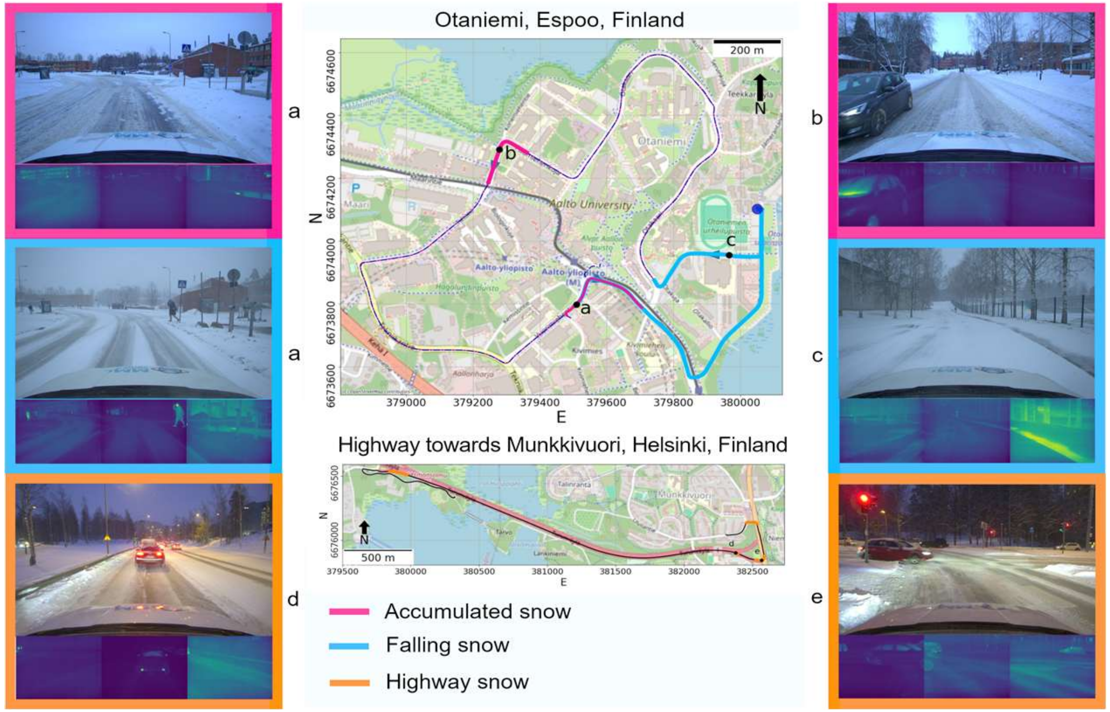
Pillar 3: Real World: Snowy Scenes





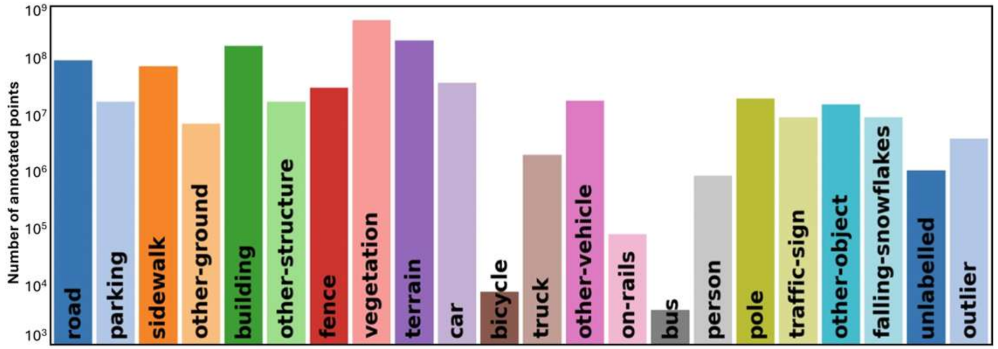
Pillar 3: Real World: Snowy Scenes

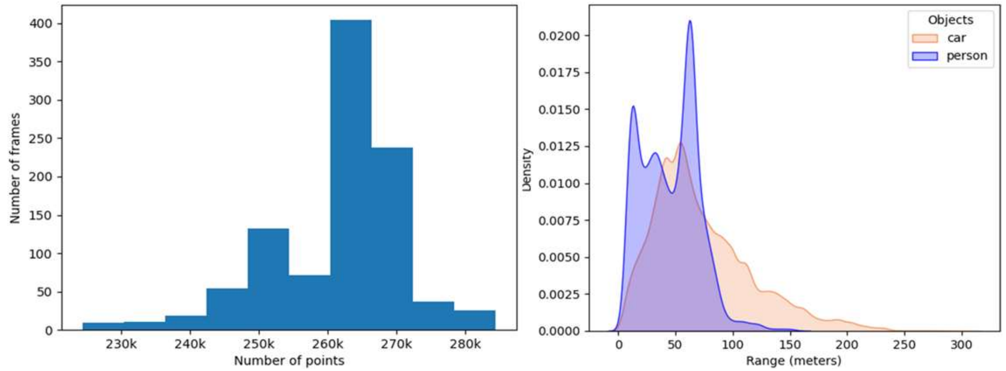
Pillar 3: Real World: Snowy Scenes



Captured over **14.4 km** of driving!

Number of annotated points per class.





Point cloud counts (left) and the object distance distribution relative to the ego vehicle (right).

Pillar 3: Real World: Snowy Scenes Exp.

- **Voxel-based models** (e.g., Cylinder3D) are more effective for semantic segmentation in high resolution point clouds. This is because voxel-based methods **maintain a consistent spatial receptive field**!
- **Projection-based methods** (SalsaNext) inherently suffer from information loss due to **the many-to-one mapping problem and geometric distortions!**
- **Point-based methods** (PTv3) operates with a fixed receptive field in terms of the number of neighboring points. Thus, as LiDAR resolution increases, **the spatial coverage of this receptive field decreases**.
- **Unsupervised point cloud denoising methods** are **not resolution agnostic** and require further study!
- **Sensor fusion boosts** detection!

De-snowing (binary segmentation)
results on the Snowy Scenes test set

Model	Type	Precision↑	Recall↑	F_1↑	IOU↑
SalsaNext [12]	SL	76.0	87.2	81.2	68.4
Cylinder3D [43]	SL	**94.7**	**89.4**	**92.0**	**85.1**
3D-OutDet [23]	SL	91.1	82.1	86.4	76.0
DROR [8]	UN	7.2	64.5	12.9	6.9
SSR [24]	UN	40.2	74.8	52.3	35.4
LiSnowNet-L1 [40]	UN	10.6	**88.6**	19.0	10.5
LiSnowNet-L2 [40]	UN	13.7	6.6	8.9	4.7
3D-UnOutDet [24]	UN	**72.4**	79.5	**75.8**	**61.0**

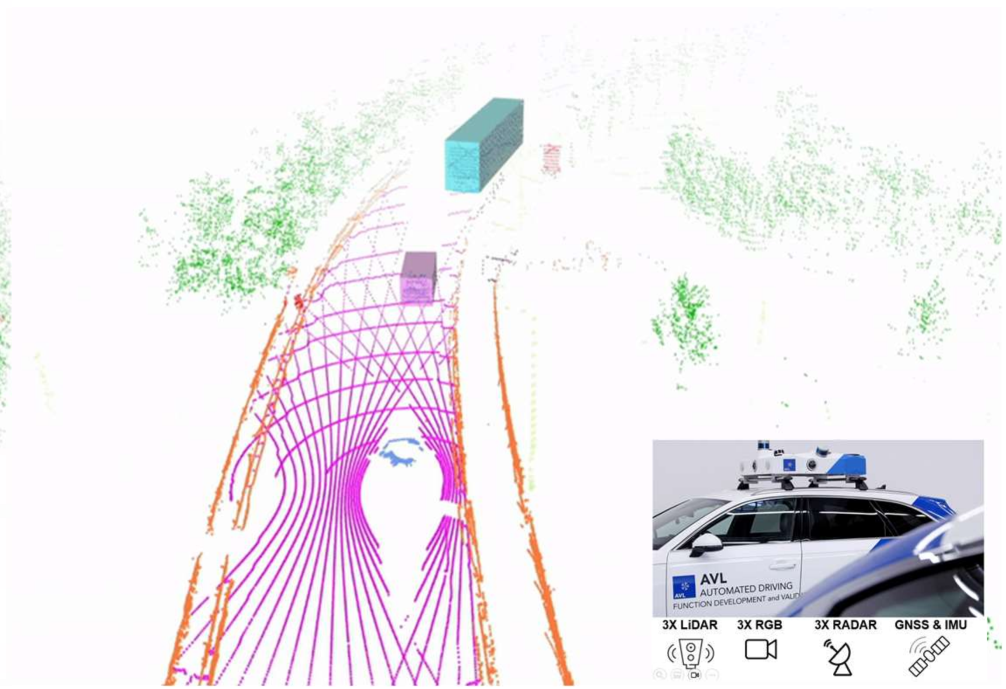
3D Car detection performance
results on the Snowy Scenes test set

Method	Modality	AP↑	ATE↓	ASE↓	AOE↓
PointPillars [21]	L	75.2	0.24	0.063	**0.280**
CenterPoint [38]	L	66.9	0.24	0.072	0.414
TransFusion-L [3]	L	**76.2**	0.23	0.097	0.391
VoxelNeXt [9]	L	74.1	**0.18**	0.064	0.530
IA-SSD [41]	L	72.1	0.20	**0.051**	0.369
Center Point (FOV) [41]	L	35.0	0.62	0.071	0.445
PointPainting [33]	LC	**82.7**	**0.14**	**0.045**	**0.157**

Multitask learning performance
on the Snowy Scenes test set

Model	mIoU↑	Car AP↑
SSMT-seg (ours)	53.4	-
SSMT-det (ours)	-	64.5
SSMT-joint (ours)	48.3	67.2

What is Next? Going from Snowy to **4 Season Scenes**



3D Semantic Segments, 3D Bounding Boxes, Noise Labeling

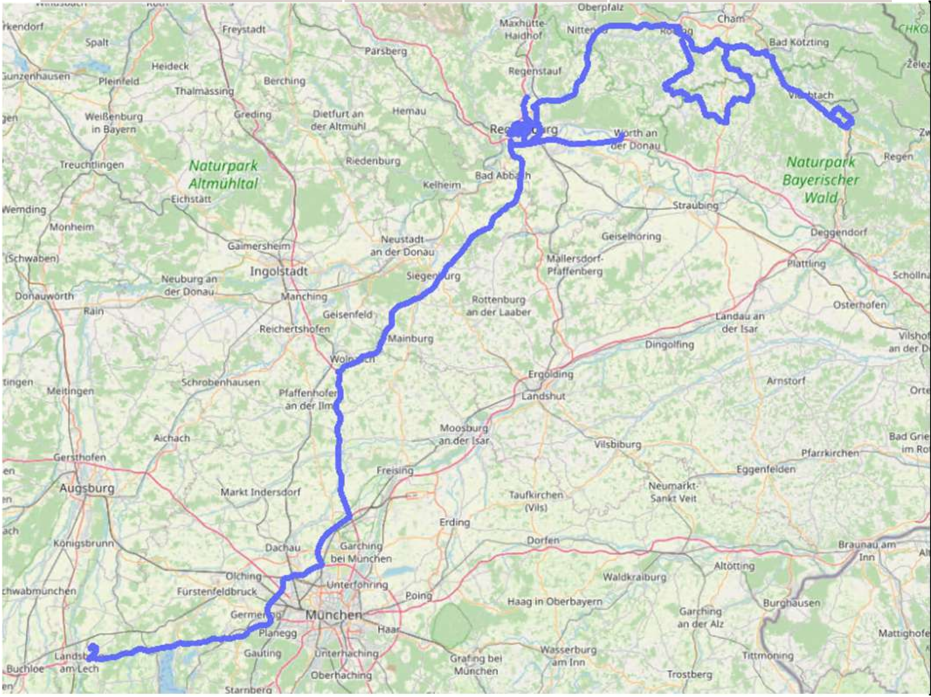
Multi-vehicle & Multi-domain

What is Next? Going from Snowy to **4 Season Scenes**

Data amount	Duration	Distance
300K (5.4 TB)	>8 hours	~800 km

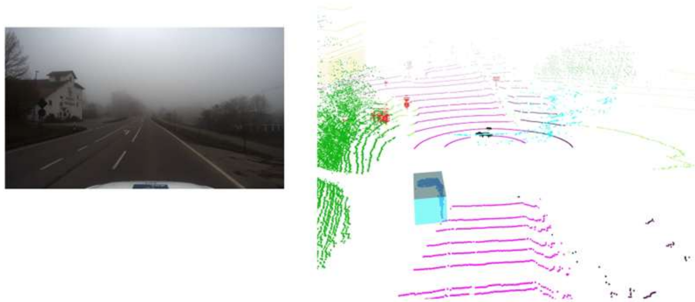
50K

Annotated Data

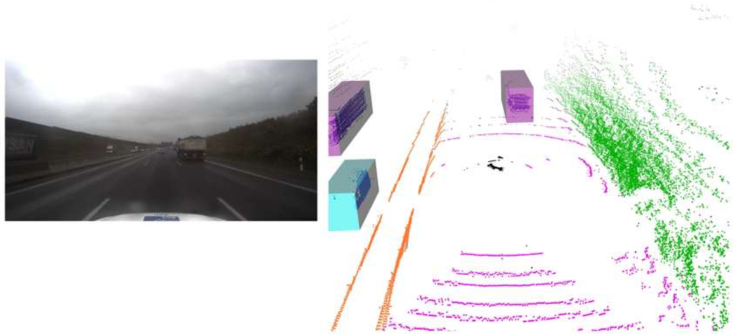


Total 300K	Weather Type					Road Type			Road Surface			Traffic Density			Time	
Sensors	Clean	Cloudy	Rain	Fog	Snow	Highway	Urban	Rural	Dry	Wet	Icy	Low	Medium	High	Day	Night
RGB	89	240	95	13	82	114	113	292	298	177	44	394	123	2	475	44
LiDAR	89	240	95	13	82	114	113	292	298	177	44	394	123	2	475	44
RADAR	89	109	27	13	82		41	279	208	68	44	294	26		276	44
GNSS	89	240	95	13	82	114	113	292	298	177	44	394	123	2	475	44
IMU	89	240	95	13	82	114	113	292	298	177	44	394	123	2	475	44

What is Next? Going from Snowy to **4 Season Scenes**



Foggy



Rainy

Snowy

Take Home Message: Be Weather aware!

- **Data is important:**
  - ***Not every kilometer driven is equal!***
  - **Limited annotated data** for harsh weather conditions (**low modality diversity** & **single perception task)**
- **New algorithmic solutions (e.g., unsupervised denoising) are required:**
  - ***Weather-aware perception and control solutions!***
  - ***Voxel-based perception models are resolution agnostic!***
  - ***Domain translation is under investigated!***

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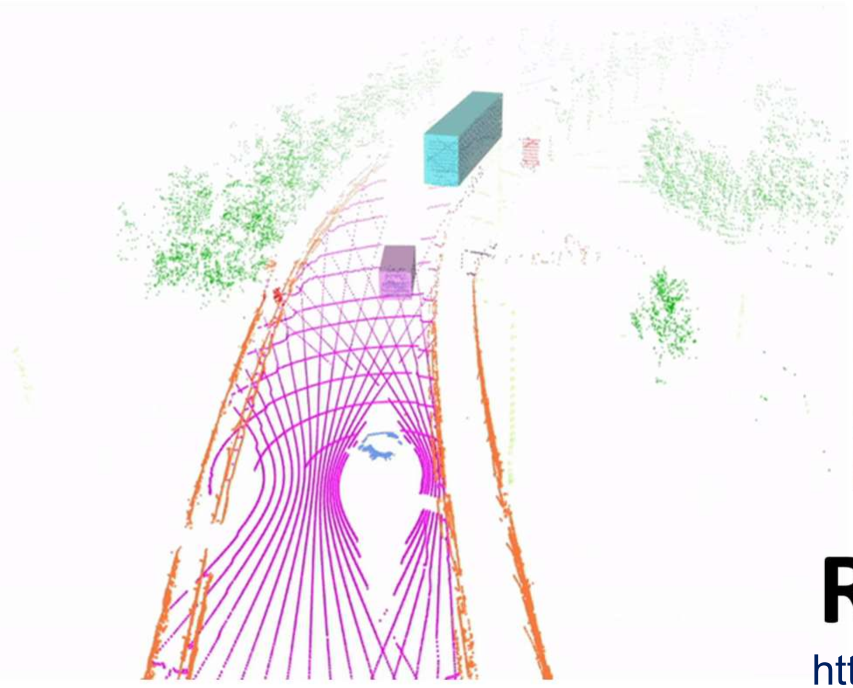
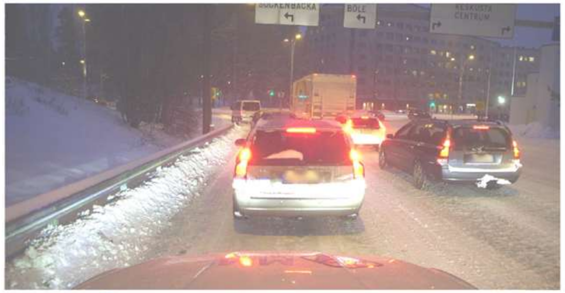
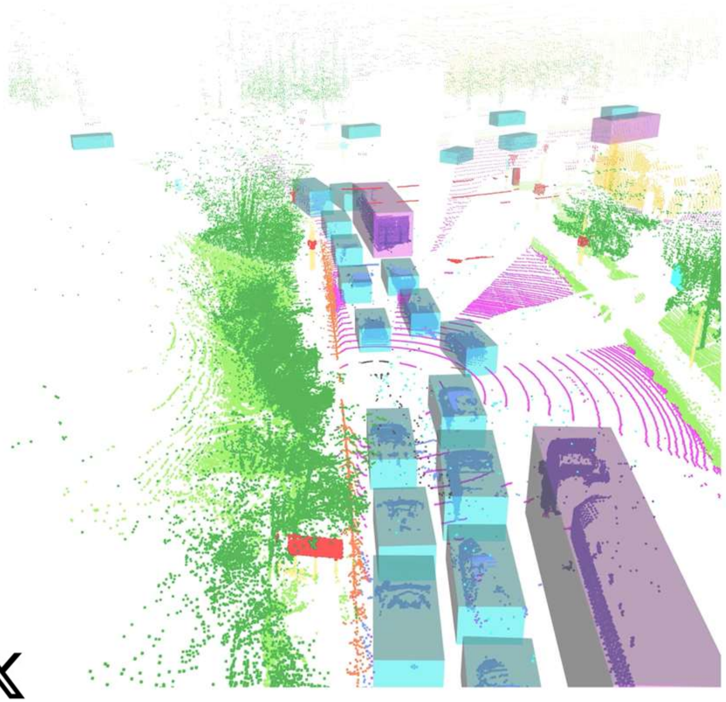
Questions
Comments







ROADVIEW

https://roadview-project.eu/

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